Barbell Trajectory Tracking for Performance Analysis During Snatch Movement in Weightlifting

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Abstract. Olympic-style weightlifting involves complex and technical movements where accurate tracking of barbell motion is crucial for performance analysis. In this paper, we present a computer vision based framework that first corrects for perspective distortion caused by varying camera height and distance, then employs a rule-based algorithm to classify snatch trajectories into four distinct types. Preliminary investigation on 6000 frames suggests 70% classification accuracy. Building on these labels, eight key barbell kinematic variables were calculated and utilized three—vertical peak height ($Y_{\max}$), initial horizontal setup (X_1), and bar drop efficiency (Y_{catch}) to generate a consolidated 0–4 performance score, mapped to five qualitative categories from "Very Bad" to "Excellent." This two fold approach, comprising trajectory classification and score calculation, was validated by a sports scientist, ensuring its reliability in helping athletes optimize lifting techniques by providing insights into barbell trajectory patterns.

Keywords: Computer Vision · Deep Learning · Injury Risk Prediction · Olympic Weightlifting · Sports · Trajectory Analysis.

1 Introduction

1.1 Background

Weightlifting is a competitive strength sport featured in the Olympic Games, where athletes attempt to lift maximum weights in two highly technical lifts: the snatch and the clean and jerk. These lifts are not only demonstrations of pure strength but also demand exceptional speed, flexibility, coordination, and balance. In the snatch, the athlete continuously lifts the barbell from the ground to an overhead position, requiring a wide grip and precise coordination to stabilize the weight overhead [1]. The clean and jerk is a two-phase lift; the 'clean' involves raising the barbell from the floor to the shoulders, followed by the 'jerk,' where the athlete propels the barbell overhead, typically using a split stance to catch and stabilize the weight [2]. Fig 1 shows both types of lifts: snatch, clean-and-jerk.

(i)

(ii)

Fig. 1: Lifts: i. A snatch being performed in competition [3], ii. A clean and jerk being performed in competition [4]

Each athlete is allowed three attempts in both the snatch and the clean and jerk. The best successful lift from each category is combined to form the athlete's total score. The athlete with the highest total in their weight class is ranked highest. In case of a tie, the lighter athlete is ranked higher [5]. Weight classes are divisions based on body mass, created to ensure fair competition among lifters of similar size. For example, as of the 2024 International Weightlifting Federation (IWF) classifications, men compete in 55 kg to 109+ kg, and women from 45 kg to 87+ kg [6]. These classes encourage inclusivity, structure competitions, and allow athletes of various body types to compete on a level playing field. While Olympic Weightlifting and Powerlifting are strength sports, Olympic weightlifting differs significantly from powerlifting. Olympic lifts emphasize explosive power, speed, flexibility, and technical precision, whereas powerlifting focuses more on maximum static strength in three lifts: squat, bench press, and deadlift [7].

A barbell is a long metal bar used in weight training and Olympic weightlifting, onto which varying weights (plates) are loaded. Standard Olympic barbells differ slightly between men's and women's categories. A men's barbell typically weighs 20 kg, measures 2.2 meters long, and has a shaft diameter of 28 mm [8].

In contrast, a women's barbell weighs 15 kg, is 2.01 meters long, and has a shaft diameter of 25 mm [8]. In the Olympics, the outer diameter of standard Olympic bumper plates is 45 cm, as defined by the IWF for all plates weighing 10 kg and above [9]. These plates are also colour-coded for easy visual identification: red for 25 kg, blue for 20 kg, yellow for 15 kg, and green for 10 kg [10]. Accurate measurement of barbell trajectory in Olympic weightlifting is essential for optimizing technique, understanding movement patterns, and preventing injuries. Deviations from the ideal path can indicate mistimed pulls or poor positioning, leading to inefficient lifts or increased injury risk [11, 12].

Studying kinematics for a weightlifter's performance and injury risk analysis is crucial. Kinematics in weightlifting refers to the study of motion without accounting for the forces behind it. It involves tracking the barbell and the lifter's body throughout the lift to assess performance. Key elements include the barbell trajectory, which reflects movement efficiency and balance; joint angles, which show how well the athlete transitions through phases; body positioning, especially of the torso and hips for power generation; and the timing of movement phases such as the first pull, transition, second pull, and catch [13, 14].

Fig. 2 shows the four types of barbell trajectories in the case of a snatch lift. Barbell trajectories are classified based on horizontal displacement relative to a vertical reference line [15]. Type 1 trajectory exhibits a "toward-away-toward" pattern, where the barbell initially moves toward the lifter, then away, and back toward the lifter, crossing the vertical reference line during the "away" phase. Type 2 trajectory also follows a "toward-away-toward" pattern but does not cross the vertical reference line at any point during the lift. Type 3 trajectory follows an "away-toward-away-toward" pattern, involving multiple crossings of the vertical reference line. Type 4 trajectory may begin with a "toward" phase, as in Type 1 or 2 trajectories, or an "away-toward" phase, as in the Type 3 trajectory. The defining feature of the Type 4 trajectory is an intervening "away-toward" phase between the first "toward" phase and the final "away-toward" phase.

1.2 Literature Review

Various methods have analyzed barbell trajectories, offering unique cost, accuracy, and practicality trade-offs. Video-based analysis is among the most accessible techniques, relying on frame-by-frame tracking from standard or high-speed cameras. Still, it is time-consuming and susceptible to human error [17]. Motion capture systems using infrared cameras and reflective markers provide high-precision three-dimensional data but are expensive, require calibration, and are limited to laboratory environments [18]. Linear position and velocity transducers offer real-time data with high sampling rates, such as Tendo units [19] or GymAware [20]. However, they typically measure only vertical displacement and cannot capture horizontal or rotational movement [21]. Smartphone applications leverage onboard sensors or video algorithms to estimate barbell velocity and trajectory; they are highly accessible but generally lack the precision of dedicated systems [22]. Mathematical and computational modeling allows for

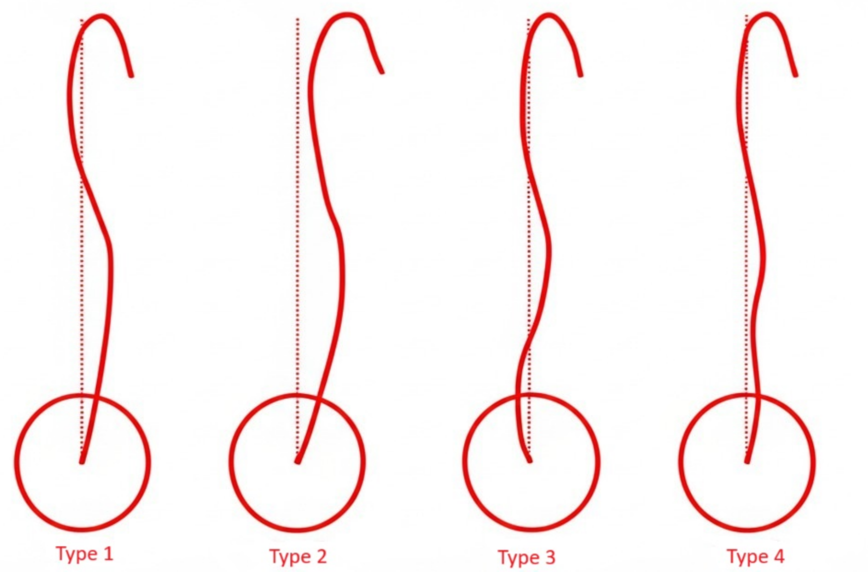

Fig. 2: Barbell trajectory types determined by the horizontal displacement pattern and vertical reference line crossing [16].

the simulation of barbell motion using kinematic and dynamic equations, providing insights into force and torque. However, the models simplify assumptions that may not reflect actual lift conditions [23]. Wearable sensors and accelerometers provide portable, real-time feedback on barbell motion, yet they may suffer from signal noise, misalignment, and require careful calibration [24].

Traditional methods for assessing barbell trajectory typically involve manual video analysis, which can be subjective, labor-intensive, and prone to human error [25]. As a result, sports scientists have increasingly turned to automated approaches for motion analysis. Automation improves objectivity and reproducibility, offering high temporal resolution and reducing workload [26]. Computer vision techniques have emerged as particularly effective tools in this domain, enabling accurate motion tracking without physical markers, which is ideal for minimally invasive performance assessment [27]. Markerless motion capture systems, powered by deep learning and pose estimation models, allow real-time analysis with reduced setup time and cost compared to traditional marker-based systems [28]. Despite these advances, most existing systems are sensitive to environmental variables and camera placement, limiting their generalization. In elite weightlifting, where minor technical differences can significantly impact performance, accurate analysis of barbell motion is essential. Studies at the 2015 World Weightlifting Championship and 2017 Pan-American Weightlifting Championship used standardized GoPro HERO4 Black camera setups to reduce measurement errors. Still, they did not account for variations in camera viewpoint, such as height and distance from the platform [16].

Considering the above limitations, the paper develops a method to classify and track barbell trajectory without the impact of camera height and distance. The paper's contributions are: i. Creating a snatch lift video dataset and developing a barbell trajectory classification algorithm based on barbell movement. ii. A module to calculate the barbell kinematic variables from video analysis. iii. Suggest a metric based on kinematic variables for performance analysis.

2 Methods

2.1 Participants

The participants were senior-level athletes, as in Olympic weightlifting, the International Weightlifting Federation and USA Weightlifting define the "Senior" age group as athletes aged 15 years and older, with no upper age limit until the "Masters" category begins at 35 years. The dataset was collected during a local competition in the United States, and it was an open-access meet. These are entry-level events, often organized by clubs or regional associations. They are accessible to many lifters, including beginners and experienced athletes. Local competitions are ideal for gaining experience and qualifying for higher-level events. A total of 44 athletes participated in the study, consisting of 28 males (mean bodyweight = 89.88 kg) and 16 females (mean bodyweight = 73.27 kg). In this paper, a random sample of the data from the total collected dataset was used for analysis. This study was approved by the Sacred Heart University Institutional Review Board, approval number IRB-FY2025-241, in April 2025.

2.2 Data Acquisition and Annotation

The data was collected during the East Coast Gold Spring Fling USA Weightlifting-sanctioned regional meet on April 12th, 2025, at Virginia Beach, Virginia, USA. A GoPro HERO10 Black action camera was employed for video acquisition due to its compact design, image stabilization, and high-resolution recording capabilities. The HERO10 features a 23MP sensor and supports video capture up to 5K at 30 frames per second (fps) or 4K at 60 fps, enabling detailed analysis of fast barbell movements [29]. The camera was placed at 3.35 meters from the barbell, and the videos were recorded at 2160p resolution. A controlled environment was established to minimize external factors affecting data quality. Subsequently, the weightlifter recorded a series of snatch lift attempts. The data collected was recorded, ensuring a diverse sample that included different weight categories and skill levels. The data included over 200 trials, with over 100000 video frames from various angles, distances, and heights. Some sample frames are shown in Fig. 3. Our study requires camera placement in a lateral plane in alignment with the barbell axis, and 10 videos from the dataset have been chosen accordingly. An expert labeled each sample video as Types 1 to 4 by observing the trajectory.

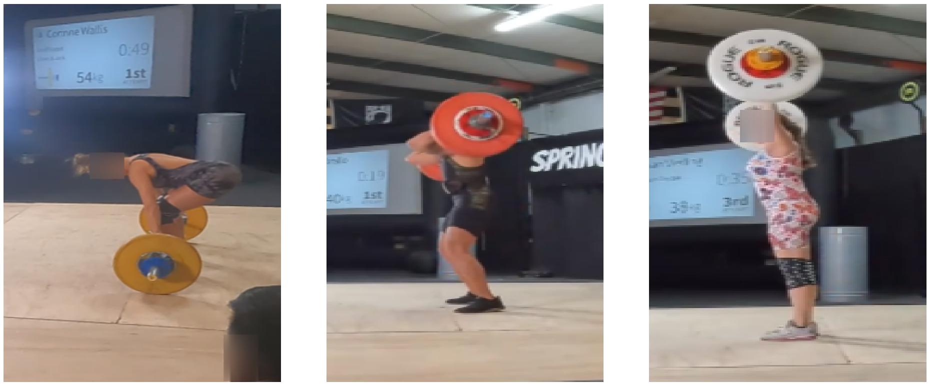

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Fig. 3: Sample data frames from the video dataset: i. Athlete starting the lift, ii. Athlete in the middle of the lift, iii. The athlete finished the lift.

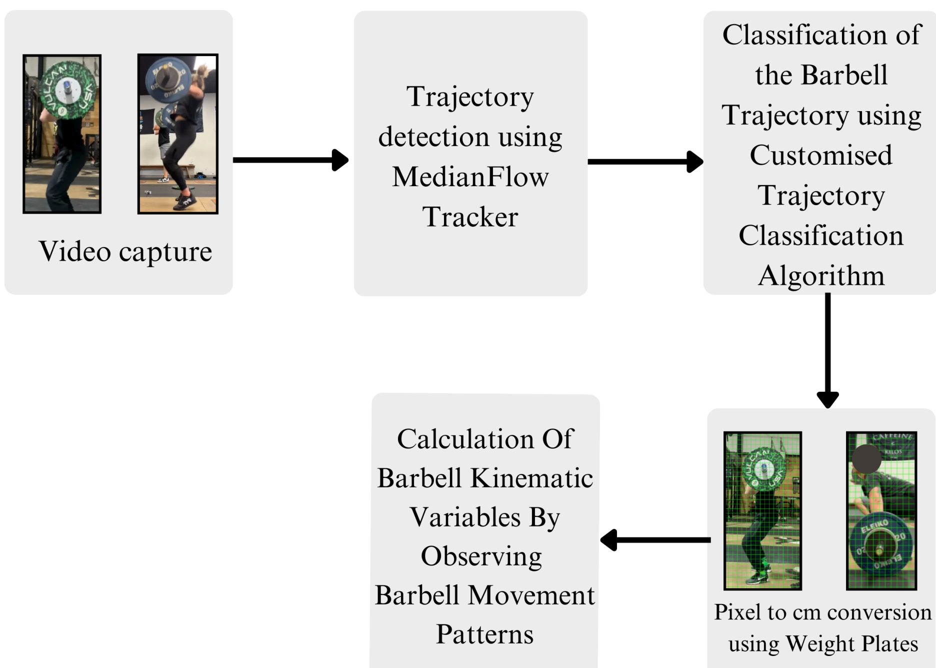


Fig. 4: The flow for video processing and calculation of barbell kinematic variables.

2.3 Video Processing and Frame Extraction

Fig.4 illustrates the overall workflow for video processing and barbell trajectory detection. After collecting the data, the videos were resized to (1920×1080) to standardize the dataset's width and height. Furthermore, as it was challenging to decide dynamically when the lift starts and ends, we trimmed the videos from the start and the end in a way that only contained the motion of the lift to avoid redundant frames. After that, the MedianFlow tracking algorithm [30] is deployed to track the movement of the snatch lift performed by the athlete. MedianFlow operates by monitoring a set of points using forward-backward error estimation. It first estimates the trajectory of each point from frame to frame, then validates the tracking consistency by comparing the forward path with the backward path, filtering out unreliable points. This makes the algorithm robust to partial occlusions and abrupt motions. The extracted coordinates obtained by tracking the snatch lift are stored in a CSV file. Subsequently, we utilize these coordinates to compute kinematic variables of the snatch lift.

2.4 Pixel to Centimeter Mapping using Weight Plates

Initially represented in pixels, the coordinates extracted from the CSV file were converted to centimeters to ensure consistency with real-world distance measurements. This transformation was essential for meaningful biomechanical analysis, as kinematic variables such as displacement, velocity, and acceleration must correspond to physical units to interpret athlete performance and assess potential injury risks [31].

To achieve this, a known reference object, the weight plate attached to the barbell, was used for calibration. A pixel-to-centimeter conversion factor was calculated by identifying the number of pixels corresponding to the visible plate diameter in the video frame.

2.5 Barbell Trajectory Classification

The study on barbell trajectory distribution varies across weight categories. The most common trajectory was Type 3, observed in 53% of lifters at the 2015 World Weightlifting Championships (WWC) and 59% at the 2017 Pan-American Weightlifting Championships (PAWC) [16]. It was particularly prevalent among heavier male lifters and top finishers. Type 2, which does not cross the vertical reference line, was the second most frequent, representing about 30% of male and female lifters. In contrast, Type 1 was less common, appearing in 13% of lifts at WWC and 8% at PAWC. The rarest trajectory was Type 4, accounting for just 6% and 3% at WWC and PAWC, respectively.

Initially, we considered classifying the barbell trajectory by training a Machine Learning (ML) algorithm. However, we decided against this approach for several reasons. First, we lacked a sufficiently large dataset to train an ML model reliably. The prevalence of Types 2 and 3 trajectory causes a data imbalance and leads to bias in Machine learning (ML) algorithms. Developing and teaching an

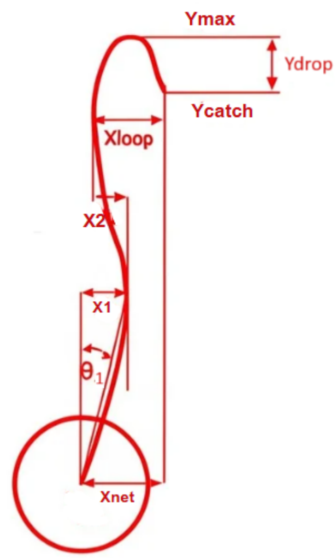


Fig. 5: Barbell kinematic variables of displacement [16].

accurate model would have been computationally intensive and time-consuming. This was unnecessary for our objective, as the classification could be effectively achieved by observing barbell movement patterns. As a result, we adopted a rule-based approach by analyzing the horizontal displacement patterns to classify barbell trajectories and determine whether the barbell crosses the vertical reference line at critical points. The classification is based on key motion parameters extracted from tracking data and described by Algorithm 1. If no matching type is found, the algorithm adds them to "unknown" for the review.

2.6 Calculation of Barbell Kinematic Variables

Eight key barbell kinematic variables are associated with the snatch lift as shown in Fig. 5. These variables help us determine whether the lift was performed accurately or whether there were chances of potential injuries. We consider the center of the barbell rod to be the origin of our analysis. The eight kinematic parameters are discussed as follows:

1) $\boldsymbol{Y_{\mathbf{max}}}$ is the highest point achieved during the lift [16]. We calculate it as the highest y-coordinate during the lift.

2) $\boldsymbol{Y_{\mathbf{catch}}}$ is the height of the catch [16]. We calculate it by finding the lowest y-coordinate post $Y_{\max}$, which happens due to the load of the weight of the barbell before the y-coordinate starts increasing again.

Algorithm 1 Barbell Trajectory Classification

```
Input: Standardized barbell trajectory coordinates
  C = [(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)]
Output: Classified trajectory type
Initialize x_negative ← False {Tracks if x becomes negative}
Initialize x_cycles ← 0 {Counts oscillations in x direction}
Initialize increasing_y ← True {Tracks if y is increasing}
Initialize phase ← "increasing" {Tracks whether x is increasing or decreasing}
for i = 2 to n do
  x ← C[i, 0]
  y ← C[i, 1]
  if x < 0 then
    if not any(C[1 : i, 0] > 0) then
      Return "Type 3"
    end if
    x_negative ← True
  end if
  if i > 2 and y < C[i − 1, 1] then
    increasing_y ← False {Y has started decreasing}
  end if
  if increasing_y then
    prev_x ← C[i − 1, 0]
    if phase = "increasing" and x < prev_x then
      phase ← "decreasing" {X starts decreasing}
    else if phase = "decreasing" and x > prev_x then
      x_cycles ← x_cycles + 1 {X starts increasing again, completing a cycle}
      phase ← "increasing"
    end if
  end if
end for
if NOT x_negative then
  Return "Trajectory Type 2"
else if x_cycles ≥ 2 then
  Return "Trajectory Type 4"
else if x_cycles = 1 then
  Return "Trajectory Type 1"
else
  Return "No matching trajectory type detected."
end if
```

3) $\mathbf{Y_{drop}}$ is the difference between $Y_{\max}$ and Y_{catch} [16]. We calculate it by the difference of y-coordinates of $Y_{\max}$ and Y_{catch}. The less the Y_{drop}, the better the athlete has performed the lift and the lower the chances of injury.

4) $\boldsymbol{X_{\text{net}}}$ is the net horizontal displacement from the start position to Y_{catch} [16]. Since the origin is at (0,0), X_{net} is simply the x-coordinate of Y_{catch}:

$$X_{\text{net}} = x_{\text{catch}} \tag{1}$$

5) $\boldsymbol{X_1}$ is the net horizontal displacement from the start to the most rearward position during the first displacement phase toward the lifter [16]. To calculate X_1, we ignore all the negative x-coordinates until the x-coordinate starts increasing. X_1 is the maximum value before the x-coordinates start decreasing.

6) $\boldsymbol{\theta_1}$ is the angle relative to the vertical reference line from the start position to the position at X_1 [16]. It is calculated as:

$$\theta_1 = \tan^{-1}\left(\frac{X_1}{y_{\text{X1}}}\right) \tag{2}$$

where y_{X1} is the y-coordinate corresponding to X_1.

7) $\boldsymbol{X_2}$ is the horizontal distance from X_1 to the most anterior position between X_1 and $Y_{\max}$ [16]. Since the x-coordinates start decreasing after X_1, we define a temporary coordinate x_{temp} as the minimum value before x-coordinates start increasing again. Then, X_2 is calculated as:

$$X_2 = X_1 - x_{\text{temp}} \tag{3}$$

8) $\boldsymbol{X_{\text{loop}}}$ is the horizontal distance from X_2 to Y_{catch} [16]. It is given by:

$$X_{\text{loop}} = x_{\text{catch}} - x_{\text{temp}} \tag{4}$$

2.7 Athlete Performance Scoring

To properly validate our method, we needed a way to measure performance after correct trajectory classification. Therefore, we measure three barbell kinematic parameters: $\mathrm{Y_{max}}$, $\mathrm{X_1}$, and $\mathrm{Y_{drop}}$ to generate a score for the lifting performance. Here $\mathrm{Y_{max}}$ shows how much vertical height the athlete generated [15], $\mathrm{X_1}$ indicates the initial barbell balance and setup [32], and bar drop relates to how efficiently the athlete transitions into the catch phase [33].

After successful trajectory classification, we check whether the barbell movement stayed within expected ranges for three parameters to generate a score. For an athlete, we generate a score out of 4, where 1 is assigned for successful classification and subsequently 1 each for three metrics if they are within the typical range observed in Olympic weight lifting; the parameter is assigned 0 if it falls outside the range. For an incorrect classification, 0 is assigned and no further processing is done. Therefore, the performance is quantified on a scale of 0 (Incorrect Trajectory) to 4 (correct trajectory and all kinematics parameters are within range). We further categorize each score value into one of the five categories - Very bad to excellent, as shown in Table 1.

Table 1: Assigning categories to the score value.

Score Value	**Interpretation**	**Score Category**
0	Incorrect Trajectory	Very Bad
1	Correct Trajectory but all parameters outside range	Bad
2	Correct Trajectory but two parameters outside range	Fair
3	Correct Trajectory but one parameter outside range	Good
4	Correct Trajectory and all parameters within range	Excellent

3 Results And Discussion

Our preliminary investigation analyzed the barbell trajectories during athletes' weightlifting sessions across 6000 frames from 10 videos.

3.1 Tracker Solution For Barbell Trajectory Detection

We experimented to detect the barbell trajectory with the help of different trackers such as Boosting, MIL (Multiple Instance Learning), KCF (Kernelised Correlation Filters), TLD (Tracking-Learning-Detection), MedianFlow, GoTurn, DlibTracker, CamShift, and Template Matching. In our study, we recorded videos directly in the athlete's lateral plane, introducing challenges such as background clutter and potential occlusions due to static objects in the environment.

Among the trackers evaluated, the MedianFlow tracker consistently provided the most accurate and stable performance, particularly in handling occlusions and maintaining robustness across frames, consistent with previous findings [34]. In contrast, other trackers showed significant limitations: Boosting and MIL failed to detect tracking losses, KCF struggled with rapid movements [35], and TLD, although accurate, was computationally intensive [36]. GoTurn required domain-specific training [37], while DlibTracker and CamShift were sensitive to speed variations and lighting changes, respectively [38], [39]. Template Matching also proved unreliable due to sensitivity to appearance changes [40].

3.2 Trajectory Classification

Our classification algorithm achieved an accuracy of 70% detecting 7 out of 10 trajectories correctly. The misclassifications in the lifts can be primarily attributed to deviations from expected barbell trajectories. In one of the lifts, the barbell did not cross the vertical reference line—a key feature for the Type 1 trajectory type, whereas in the other, it did, leading to confusion between types. Additionally, for one of the cases, the detected trajectory did not align with any predefined types. These discrepancies likely stem from non-standard execution by the athletes, technical errors during the lift, or observational error by the annotator, ultimately leading to incorrect classification outcomes.

3.3 Kinematic Parameter Extraction

The average height measured by our measurement is 173.33 cm, which is in close accordance with the average height of 175.26 cm [16] for male weight lifters in the USA. The average values of kinematics across 6000 frames are shown in Table 2. Here we compare the average values of the kinematic parameters with the typical range [16, 41, 42] observed in elite weight lifters to check measurement efficacy. All these ranges are proportional to the athlete's height. For valid comparison, measurements are normalized with respect to athlete height. $\mathrm{Y}_{\mathrm{max}}$ and $\mathrm{Y}_{\mathrm{catch}}$ are primary vertical measures, with $\mathrm{Y}_{\mathrm{drop}}$ indicating efficiency. $\mathrm{X}_{\mathrm{Net}}$, X_1, X_2, and $\mathrm{X}_{\mathrm{loop}}$ describe horizontal movement and should be minimum for best techniques. Angle θ describes the bar path and the lifter's mechanics. These ranges provide a robust framework for analyzing and comparing kinematic parameters in Olympic snatch and lift trajectories. For example, efficient lifts (Type I trajectory) typically show minimal $\mathrm{X}_{\mathrm{Net}}$, small $\mathrm{Y}_{\mathrm{drop}}$, and smooth transitions between phases. We can observe from Table 2 that all average values of parameters are within the range, ensuring fidelity of CV-based measurement.

Table 2: Average values of kinematic parameters and their typical range in Olympic snatch and lift [16, 41, 42] normalized to average athlete height estimated from 10 videos. The average estimated height is 173.33 cm.

Parameter	**Average Value**	**Typical range %**	Typical range (cm)
$\mathrm{Y}_{\mathrm{max}}$ (cm)	133.00	70 - 85	120 - 145
$\mathrm{Y}_{\mathrm{catch}}$ (cm)	125.22	60 - 75	100 - 130
$\mathrm{Y}_{\mathrm{drop}}$ (cm)	07.78	04 - 15	6.5 - 25
$\mathrm{X}_{\mathrm{net}}$ (cm)	23.61	00 - 10	00 - 17
X_1 (cm)	05.11	02 - 06	03 - 10
θ_1 (degrees)	04.44	05 - 15	–
X_2 (cm)	08.17	02 - 08	03 - 14
$\mathrm{X}_{\mathrm{loop}}$ (cm)	02.76	02 - 07	03 - 12

3.4 Trajectory Detection and Performance Score

The results of 10 videos are summarized in Table 3. For each video, the table compares the trajectory type identified by subject matter experts with the predicted type obtained from our algorithm. It also shows the estimated height of the athlete using computer vision and values for three kinematics parameters. The score is computed by checking whether Y_{max}, X_1, and Y_{drop} falls in the designated range as indicated in Table 2.

From Table 3, we observe that for athletes 1, 2, and 6, the trajectory could not be correctly classified and therefore, they were assigned a 0 score or a very bad category. We can see that most athletes showed good vertical barbell displacement, with Y_{max} values that matched well with their respective heights and falls in the range of 120 - 145 cm. This suggested that they could generate sufficient vertical force during the lift. X_1, representing the initial horizontal position, was within the ideal range (3 - 10 cm) for most lifts, except for athletes 5 and 7, indicating a proper starting setup for them. For athletes 5 and 7, the score is 3, or category Good is generated due to X_1 falling outside the ideal range. Similarly, the bar drop (Y_{drop}) was in the expected range of 6.5 - 25 cm for efficient catch mechanics in most cases. Overall, athletes 3, 4, 8, 9, and 10 had a score of 4 or excellent category lifts, as they consistently had Y_{max}, controlled X_1 displacement, and optimal bar drop values.

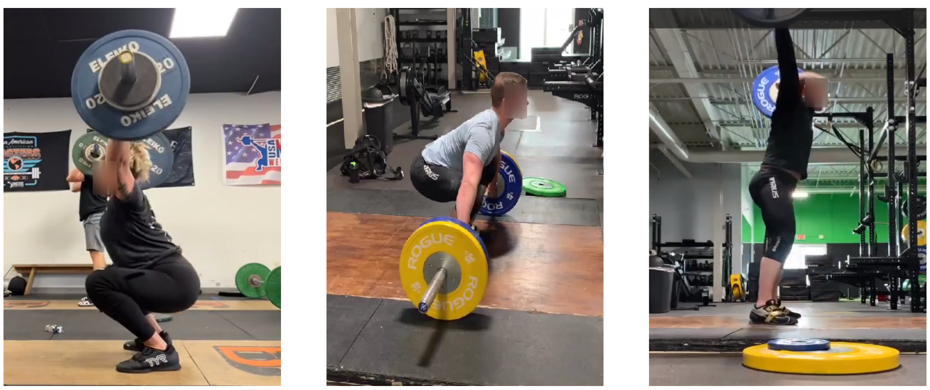
Table 3: Classification, barbell kinematic parameters validation, and Performance score. The boldface indicates incorrect classification or a parameter not in the range. Cat. indicates the category of the score.

Athlete	**Type Given**	**Type Predicted**	**Height of Athlete cm**	$\mathbf{Y_{max}}$ **cm**	X_1 **cm**	$\mathbf{Y_{drop}}$ **cm**	**Score & Cat.**
1	1	**2**	165	129.0	5.0	8.0	0 & Very Bad
2	2	**1**	170	133.5	1.5	9.5	0 & Very Bad
3	3	3	174	137.0	3.5	14	4 & Excellent
4	3	3	179	139.5	8.0	4.5	4 & Excellent
5	3	3	185	139.5	**11**	6.0	3 & Good
6	4	–	–	–	–	–	0 & Very Bad
7	2	2	170	133.5	**3.0**	6.5	3 & Good
8	1	1	177	139.0	5.0	6.0	4 & Excellent
9	1	1	178	136.0	3.5	7.0	4 & Excellent
10	1	1	162	126.0	5.5	8.5	4 & Excellent

3.5 Limitations of the proposed approach

The reliability of the proposed approach is based on certain assumptions. One major limitation is the dependency on the manual drawing of the bounding box annotations around the barbell. Some vision-related challenges are shown in Fig. 6. Occlusions from external objects in the background led to tracking failures or inaccuracies. Additionally, the method assumes that the camera is positioned laterally in line with the athlete performing the lift. When the videos are captured from a high angle (20 degrees or more), this assumption breaks down. This would need preprocessing of videos to correct the affine transformation. Furthermore, tracking continuity was lost if the barbell moved out of the camera frame due to improper field of view.

Another major issue arose when another athlete performed a different movement behind the main subject, causing the tracker to lock onto the background motion instead of the barbell incorrectly. Lastly, an excessively high frame rate introduced motion blur and unnecessary frame redundancy, making it challenging to extract precise kinematic variables of the barbell. Since the approach relies on pixel-level measurements to classify trajectory patterns and calculate derived metrics, the resulting perspective distortions lead to improper trajectory classification and reduce the interpretability of the results. The performance score could be made more discriminative with the addition of features like velocity and total power in the lifts. These challenges highlight the need for careful camera placement, appropriate frame rate selection, and improved tracking methods to enhance accuracy in motion analysis.



(i) (ii) (iii)

Fig. 6: Tracking Challenges: i. Occlusion due to the background person, ii. Video taken from an angle, iii. The barbell is going out of the camera plane.

4 Conclusion and Future work

Incorrect posture while lifting weights significantly affects athletes' performance and careers. Our proposed approach demonstrates strong predictive capabilities for identifying risk factors and achieving high precision. Preliminary tests on additional video samples suggest that the framework can be generalised to achieve similar results; however, broader validation is required.

Future work will focus on expanding the dataset and incorporating advanced detection techniques, such as automating the pixel-to-centimetre conversion and mitigating affine transformation effects through camera calibration. Manual bounding box initialization will be replaced by real-time object detection to streamline the process.

To enhance adaptability to subtle variations in lifting styles, the current rule-based classifier will be replaced with a machine learning-based model trained on a larger and more diverse dataset, improving trajectory classification accuracy. The analysis will be extended beyond snatch movements to include other Olympic lifts, such as the clean and jerk.

Deployment on mobile applications is planned to facilitate real-time analysis, increasing accessibility for athletic training and injury prevention. Finally, the performance metric will be made more holistic by incorporating velocity and power measurements.

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