A Framework for Biomechanical Analysis of Jump Landings for Injury Risk Assessment

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***Abstract*—Competitive sports require rapid and intense movements, such as jump landings, making athletes susceptible to injuries due to altered neuromuscular control and joint mechanics. Biomechanical features during landings are associated with injury risk, emphasizing proper movement and postural stability. Computer vision techniques offer a time-efficient, non-invasive, and unbiased method to assess jump-landings and identify injury risks. This study proposes a video analysis framework to evaluate jump landing biomechanics in athletes to determine irregular movements and incorrect postures. It provides advice and recommendations to coaches for injury prediction and training improvements. The proposed framework is tested using countermovement jump videos of 17 NCAA Division I female basketball athletes. The results indicated a low Mean Absolute Error (0.97), high correlation (0.89), high average accuracy (98.31%) and F1 score (0.98), signifying the framework's reliability in identifying injury risk.**

***Index Terms*—Basketball, biomechanical assessment, collegiate athletes, computer vision, jumps, injury**

I. Introduction

In sports, prolonged high-intensity repetitive movements and asymmetric postures increase the risk of athlete injuries [1]. This increased risk is attributed to altered or reduced neuromuscular control during sports movements, leading to lower limb joint mechanics changes, including motions and loads [2]. Jump landing is one such frequent movement in a sport like basketball. In a game or practice session, an athlete performs 70 jumps per hour on average, and they experience severe ground reaction forces increasing injury risk [3], [4]. Consequently, assessing and evaluating their movements for timely intervention is essential.

Knee kinematics, such as knee flexion, internal/external rotation, and knee valgus position, are primary predictors of anterior cruciate ligament (ACL) injury risk [5]. Less knee flexion, greater knee internal rotation and abduction, and poor trunk stability are associated with a higher risk of knee injury [6], [7]. In basketball, stance width is the distance between the player's feet and impacts injury risk [8]. A wide stance prevents agility, while a narrow stance compromises stability and control. Foot rotation positions during landings influence knee-joint loading. Both toe-in (internal) and toe-out (external) rotation leads to a higher knee valgus moment, which is associated with an increased risk of injury [9].

Jump landing tests assess injury risk by evaluating neuromuscular control, stability, and movement patterns. Tests like Drop Jump (DJ), Single-Leg Drop Jump, and Vertical Jump focus on management and mechanics [10]. Tuck Jump examines form and control in consecutive jumps, while Landing Error Scoring System (LESS) evaluates landing mechanics for ACL injury risk prediction [11]. The hop test measures lower limb strength and symmetry, and isokinetic strength testing focuses on the quadriceps and hamstring muscles.

The conventional approach poses challenges due to the high amount of labor, lack of efficiency, and inter-expert variability [14]. Computer vision (CV) and machine learning (ML) [15] provide time-efficient, low labor, non-invasive, and unbiased techniques for assessing jump-landings [16]. N. Blanchard et al. [17] presented a video dataset with DJ and countermovement-jump (CMJ) landings to evaluate ACL injury risk. C. Roygaga et al. [18] analyzed DJ and CMJ videos to identify 14 errors automatically. Hébert-Losier K et al. [19] used CV for LESS measurement using jumps videos. We note that the existing injury risk assessment techniques are either (i) specific to the type of jump evaluation test performed; (ii) specific to the type of injury to be identified, or (iii) specific to the scoring system used as a screening tool for injury risk.

Using videos, the proposed generic framework looks at overall movement quality and patterns, assessing symmetry, coordination, and fluidity during jump-landing and other functional movements. By allowing for consistent data collection and interpretation, it provides a standardized approach to evaluate athletes' movement patterns and injury risk across various tests and screening tools. As an outcome, it identifies common movement and posture deficiencies. The main contributions are the following aspects of this proposed generic framework: 1. Reproducible, high-risk lower extremity joint biomechanical assessment identifying incorrect positioning and dynamic stability-related errors at initial contact and maximal displacement during jump landings, using a two-camera setup in frontal and sagittal planes. 2. Field implementation and validation of the proposed framework over 17 NCAA Division I female basketball 'athletes' using CMJ jump videos. 3. 'Athletes' lower-limb progression analysis over the season provides theoretical guidance to coaches for decision-making.

II. Proposed Framework

Two cost-effective standard video cameras are utilized to record the jump-landing task. These cameras are placed 345.40 cm in front of and to the side of the jump spot [11]. MediaPipe Pose (MPP) processes the recorded video and extracts kinematic features. It is an open-source, cross-platform framework by Google, integrated with OpenCV [20]. Fig. 1 outlines various stages of the proposed framework.

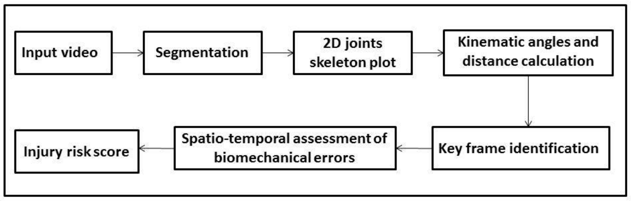

Fig. 1. Proposed framework.

The video is first segmented into individual frames, and each frame is converted from BGR to RGB format for maintaining compatibility with MPP. It utilizes ML, and BlazePose [20] to estimate 2D coordinates of movements and posture, defining body landmarks (body joints) in each frame. From the 33 body landmarks identified, as shown in Fig. 2, we utilize 13 (0, 11, 12, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32) for kinematic feature estimation.

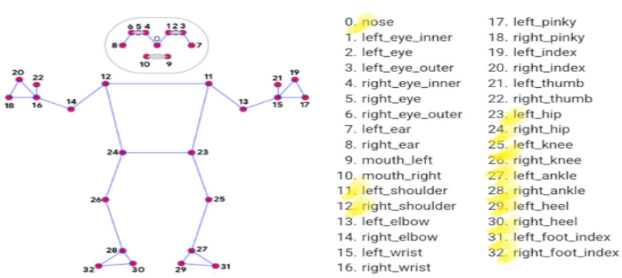

Fig. 2. Definition of body landmarks in MPP [20]. The highlighted landmarks are used in the proposed work.

These coordinates acquired through MPP are first normalized by multiplying the y-axis pixel values by the inverse ratio. In the next step, we compute kinematic features for each frame – a mixture of angles between body landmark key points and ratios between distances using the Euclidean distance and Cosine angle. It includes angles for knee flexion, hip flexion, ankle plantar flexion, knee valgus position, trunk flexion, lateral trunk flexion, foot rotation, feet stance width, and shoulder distance in each frame. Now, we use the method described in Fig. 3 to identify the frames of interest from the video. The primary method is to track the ankles across frames to detect the frame when landing occurs as initial contact (IC) frame. We additionally track the hip, knee, and ankles to calculate the knee flexion angle over frames to determine the frame with maximum knee flexion (KF_{max}) after landing.

Algorithm: Keyframe identification

Input: Frontal and lateral Videos for a jump-landing trial
Output: IC frame and KF_{max} frame

i. Obtain the body-part key points in each frame in both frontal and lateral videos using MediaPipe.

ii. For IC frame:
   a. Place a horizontal reference line parallel to the jump spot.
   b. Find the Euclidean distance between ankle coordinates and a perpendicular reference point on the reference line segment for each frame.
   c. Identify the frame with the highest distance, corresponding to the peak-of-jump.
   d. The frame with the least distance after the peak is considered the IC frame.

iii. For KF_{max} frame:
   a. Calculate the left and right knee flexion angles using the cosine angle of the known three-point coordinates.
   b. After identifying the IC frame, determine the frame with the highest knee flexion angle following the IC frame.

Fig. 3. Method for keyframe identification.

In the next processing stage, we identify irregular movements and incorrect postures quantified in terms of 12 jump-landing errors using the extracted kinematic features from both frontal and lateral videos. They are discussed as follows.

A. Knee Flexion at IC

We compute the left (23, 25, 27) and right (24, 26, 28) knee flexion angles using the cosine of the known three-point coordinates (hip, knee, ankle) as shown in Fig. 4i. If either of the knee flexion angles is less than 30°, it is an error.

B. Knee valgus position at IC

We assume two straight lines: one connecting the hip and center of knee key points and the other connecting the centers of knee and ankle key points. The angle between these lines provides information about knee valgus aberrations (Fig. 4ii). If the angle measures approximately 0° or 180°, it indicates no error in the knee alignment.

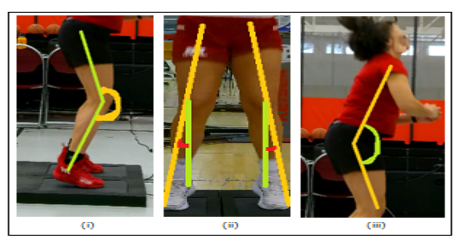

Fig. 4. Jump-landing errors :– i. knee flexion, ii. knee valgus position, iii. trunk flexion

C. Trunk flexion at IC

We calculate the left (11, 23, 25) and right (12, 24, 26) trunk flexion angles using the cosine of the known three-point coordinates (shoulder, hip, knee). Following this calculation, if either of the trunk flexion angles measures approximately 0° or 180°, it is considered an error.

D. Lateral trunk flexion at IC

We assume two straight lines: one from the hip midpoint to the top of the frame and the other connecting the hip midpoint to the shoulder midpoint. It is an error if the angle between these two lines does not equal 0° or 180° (Fig. 5i).

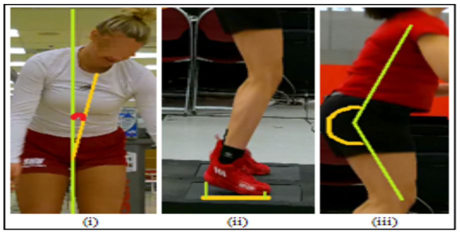

Fig. 5. Jump-landing errors:– i. lateral trunk flexion, ii. ankle plantar flexion, iii. hip flexion.

E. Ankle plantar flexion at IC

We acquire the coordinates of the left and right heels (29, 30) and the $foot_{index}$ (31, 32). If the y-coordinate of the heel is smaller than the $foot_{index}$ for one foot or both feet, it indicates a heel-to-toe landing, which signifies an error (Fig. 5ii).

F. Hip flexion at IC

We calculate the left (11, 23, 25) and right (12, 24, 26) trunk flexion angles (Fig. 3iii) using the cosine of the known three-point coordinates (shoulder, hip, knee). Following this calculation, if either trunk flexion angle measures approximately 0° or 180°, it is considered an error (Fig. 5iii).

G. Foot externally / internally rotated at IC

We assume a straight line from the heel point to the bottom of the frame to establish a reference and another straight line connecting the heel and $foot_{index}$ key points. It indicates an error if the angle between these two lines is greater than 30° externally or internally (Fig. 6i).

H. Stance width at IC (wide/narrow)

We first calculate the Euclidean distance between the left and right shoulder key points (11, 12). Next, we calculate the Euclidean distance between the left and right ankle key points (27, 28). If the ratio of shoulder to feet distance is greater than 1, it indicates a narrow stance error. On the other hand, if the ratio of shoulder to feet distance is less than 1, it signifies a wide stance error (Fig. 6ii).

Fig. 6. Jump-landing errors:– i. foot rotation, ii. stance width, iii. feet landing symmetricity.

I. Feet landing symmetricity at IC

In optimal jump-landing, the feet should land toe-to-heel. To assess this, we examine the y-coordinate of the left and right $foot_{index}$ (toe) from the IC frame. Suppose the y-coordinates of the two feet are not equal; in that case, it indicates that they did not land simultaneously, which is considered an error (Fig. 6iii).

J. Knee, Trunk and Hip flexion displacement from IC to KF_{max}

It is an error if the knee flexion angle displaces less than 45° between IC and KF_{max}. If the trunk is more flexed at KF_{max}, then IC results in an error. Also, it is an error if the hip is more flexed at KF_{max} than IC.

III. Experimental Setup

A. Participants

17 NCAA Division I female basketball athletes (mean [standard deviation]: n = 17, age = 21.00 [±3.00] years, height = 174.21 [±19.27] cm, body mass = 73.98 [±11.52] kg) participated in this study. All the athletes were Sacred Heart University, USA's women's basketball team members. The Institutional Review Board (IRB) approved the research, and all the subjects were informed and consented before participating (IRB approval number 170720A on 09/14/2020).

B. Study Design

We used two Panasonic LUMIX FZ80 - 4K digital cameras offering a high resolution and stabilization for recording the videos from frontal and lateral planes as the athletes performed CMJ over force plates as a part of their regular training routine. As instructed, they placed their hands on their sides, conducted a deep squat, and executed a maximal jump height to optimize their training results. Each CMJ session was consistently scheduled on the same day of the week, usually on Monday or the first training day. The recorded videos were analyzed using our framework to identify lower extremity movement and postural errors and quantify them using the landing error scoring system (LESS). The framework can compute any score based on lower extremity measurement, and we use LESS to demonstrate its performance. We simultaneously made an expert (blinded to framework generated score) annotate these videos with LESS by replaying them over the software Kinovea [21] (version 0.8.25, www.kinovea.org). The framework-generated score was compared to the expert annotated score to validate the efficacy of the proposed generic framework.

C. LESS mapped to the proposed framework

LESS is a reliable movement and posture screening tool for jump-landing tasks that help identify errors associated with ACL and other lower-extremity injury mechanisms [11]. It comprises 17 evaluation parameters that are potential errors, and a score (range 0 to 17) greater than 5 indicates poor landing biomechanics and a higher relative risk of sustaining non-contact lower-extremity injuries. Among the 17 parameters, the first 15 indicate individual errors, while the final 2 are subjective and derive scores from the initial 15's errors. The initial 15 LESS parameters correspond to the proposed framework's identified errors – 1-Knee flexion IC (A), 2-hip flexion IC (D), 3-trunk flexion IC (C), 4-ankle plantar flexion IC (F), 5-knee valgus IC (B), 6-lateral trunk flexion IC (E), 7-stance width (wide) IC (H), 8-stance width (narrow) IC (H), 9-foot (toe-in) (F), 10-foot (toe-out) (F), 11-symmetric foot contact IC (I), 12-knee flexion displacement (J), 13-hip flexion at KF_{max} (L), 14-trunk flexion at KF_{max} (K), 15-knee valgus displacement (B). For 16-joint displacement, we assigned a score of 0 if no errors (I, J, K) were present. A score of 1 is given for one error and a score of 2 for two or all three errors. Similarly, for the 17-overall impression, if parameters 1 to 16 have no errors (0), a score of 0 is given. A score of 1 indicates two or fewer errors, while a score of 2 reflects more than two errors in parameter 17.

Errors	Expert Annotation		Framework Generated		Accuracy Percentage	F1 Score
	Error	No Error	Error	No Error		
Knee flexion IC	0	42	0	42	100%	1.00
Hip flexion IC	0	42	0	42	100%	1.00
Trunk flexion IC	1	41	1	41	100%	1.00
Ankle plantar flexion IC	7	35	7	35	100%	1.00
Knee valgus IC	11	31	12	30	95.23%	0.95
Lateral trunk flexion IC	8	34	11	31	92.85%	0.93
Stance width (wide)	7	35	7	35	100%	1.00
Stance width (narrow)	4	38	4	38	100%	1.00
Foot (toe-in)	4	38	4	38	100%	1.00
Foot (toe-out)	2	40	2	40	100%	1.00
Symmetric foot contact IC	7	35	8	34	97.61%	0.98
Knee flexion displacement	0	42	0	42	100%	1.00
Hip flexion at KF_{max}	0	42	0	42	100%	1.00
Trunk flexion at KF_{max}	0	42	0	42	100%	1.00
Knee valgus displacement	9	33	12	30	92.85%	0.93
Joint displacement	6	36	8	34	95.23%	0.95
Overall impression	5	37	6	36	97.61%	0.98

Fig. 7. Detection accuracy for LESS errors in IC and KF_{max} frames.

D. Results and Discussion

Eighty-four videos (42 frontal; 42 lateral) were analyzed. The mean LESS score, as rated by the expert, was 4.78 + 1.24, and that generated by the proposed framework was 4.80 + 1.15. A low mean absolute error (MAE) of 0.97 and a high correlation (r) of 0.89 were observed between the framework-generated and expert-annotated LESS scores. Fig. 7 shows the accuracy percentage and F1 score for each type of error. The framework successfully detects errors (1, 2, 3, 4, 7, 8, 9, 10, 12, 13, 14) with 100% accuracy and an F1 score of 1.00. However, accuracy and F1 scores for errors 5, 6, 11, and 15 are lower due to strict thresholding in the framework than expert annotations. Errors 16 and 17 are subjective and rely on errors 1-15, contributing to the disparity between expert annotations and framework-detected errors.

Knee flexion angle is a crucial biomechanical factor in predicting injury risk in sports involving jumping and landing, such as basketball [3]. While inadequate knee flexion increases stress on the knee joint, making it more susceptible to injury, proper knee flexion landing helps distribute forces evenly across the lower extremity, reducing the risk of overloading. In rehabilitation, monitoring and improving knee flexion angle is crucial for minimizing re-injury risk and promoting a safe return to play [22]. Therefore, we tracked athletes' KF_{max} angle over weeks to assess their alignment progression over the season.

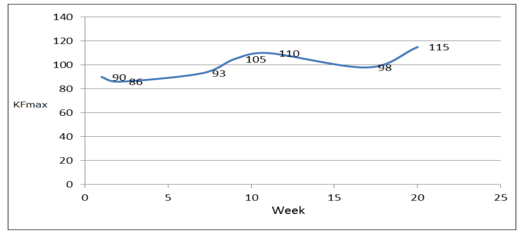

Fig. 8. Athlete's KF_{max} angle progression over the season.

A KF_{max} angle of 87 to 110 helps athletes achieve maximal vertical jump height [23]. Fig. 7 shows an athlete's KF_{max} angle over a season. It can be observed that KF_{max} is in an optimal range at the beginning of the season. As the season ends, we see the KF_{max} value above the optimal threshold, reflecting fatigue caused due to undertraining or overtraining. These weeks are game weeks when athletes travel more, play games and exercise less.

IV. Conclusion

Lower extremity injuries have severe consequences on athletes' performance and their careers. Hence, coaches aim to prevent these injuries through neuromuscular monitoring and guided training programs. The proposed framework helps coaches to identify risky movements and incorrect postures. It balances the expensive, time-constrained 3D motion analysis technique and the intra- and inter-rater variability-constrained clinician-driven screening. It achieves a low MAE of 0.97, a high correlation of 0.89, and a high average accuracy (98.31%) and F1 score (0.98) with expert annotations, making it a reliable assessment tool. On average, the proposed framework can process a single video and generate injury-risk score within a span of 102 seconds (can reduce further on better configuration machines). Jump tests are common in several sports, such as basketball, volleyball, and soccer, to evaluate athlete readiness. The two-camera set-up can easily be deployed in athletic training facilities to broaden the use of the framework. This generic framework will promote collaboration among sports professionals, leading to the development of evidence-based injury prevention strategies applicable across multiple sports and populations. In the future, we aim to use the framework for tracking 'athletes' lower limb progression over a season for injury-risk assessment, monitoring recovery, and a safe return to play.

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