Landing Error Scoring System for Basketball: A Computer Vision Approach

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***Abstract*—The Landing Error Scoring System (LESS) method is used in sports, but scoring requires a lot of time, depends on the clinician, and is typically unavailable to athletes in lower divisions of competition. An objective, non-invasive, and time-efficient way to evaluate jump-landings and determine damage risks is through the use of computer vision techniques. Our aim is to automate those LESS scores using a deep-learning-based computer vision approach. We use the countermovement jump video of one of the athletes out of the 17 NCAA Division I female basketball athletes to identify the potential injury risk.**

***Index Terms*—image processing, computer vision, LESS, athletes, basketball, injury**

I. INTRODUCTION

Sports with high-intensity, repetitive and asymmetric postures tend to increase the likelihood of injuries [2]. Jump landings are one of the many movements which are associated with athletes injury risks. Evaluating the jump landings and scoring them based on a standardized scoring system (LESS) to assess injury risk becomes a valuable tool. The values of knee flexion, stance width, internal/external rotation are major predictors of anterior cruciate ligament (ACL) injury risk [3]. Furthermore, lateral trunk flexion for an athlete becomes an important tool to measure the readiness of the athlete to participate in the sport after an injury [4].The extreme labor-intensive process of physically assessing jump landing scores through LESS, can be simplified by using Machine Learning (ML) and Computer Vision (CV) [5]. We consider the two primary metrics for injury risk through LESS, Lateral trunk flexion and Stance width. Through consistent data collection through video frames fragmented into individual frames, we standardize the method to calculate the respective error score through the computer vision methods. Moreover, we have validated the scoring system with the existing dataset from [1]. These scores would then be fed into a Deep Learning model to learn the existence of lateral flexion as well as the width of the stance.

II. METHODOLOGY

A. Frame Extraction

We used a video of 35 seconds for the evaluation of a single athlete, we extracted the frames at a rate of 5.8 frames per second to get 203 frames from the 35 second video. All of these frames were then fed into the MediaPipe Pose highlighting the necessary key points.

B. Key Point Extraction

As mentioned above, we used MediaPipe Pose for getting the essential key points from the body to calculate the lateral trunk flexion and the stance width. We did a comparative and feasibility analysis on different human pose estimation frameworks by reviewing [6].

C. Calculation and Annotation

We annotate the frames with the key points after calculating the lateral flexion and stance width. We draw a a straight line from shoulder midpoint to ankle midpoint, we draw another straight line from hip midpoint and ankle midpoint. The angle between these lines is the lateral trunk flexion. If the angle isn't 0 or 180, the lateral trunk flexion is present. Similarly for Stance width, we calculate the Euclidean distance between the two points of right ankle and left ankle, and the Euclidean distance between the right shoulder and left shoulder. The ratio of shoulder distance to ankle width is the stance width of the athlete. If the ratio is between 0.8 to 1.2 then it is normal stance, whereas a ratio greater than 1.2 is narrow stance and less than 0.8 is wide stance.
We used roboflow for annotating the frames and for creating the bounding boxes, these images will be later used as ground truth for a deep learning model to learn the presence of lateral trunk flexion and the values of stance width.

TABLE I
FRAME CHARACTERISTICS

Frame Number	Lateral Flexion		Stance Angle	Type (Normal/Wide/Narrow)	Ratio
	Present?	Right/Left/None			
51	Yes	Left	0.37382	Normal	1.057934
52	Yes	Left	1.278972	Normal	1.061781
54	Yes	Right	1.509883	Normal	1.152186

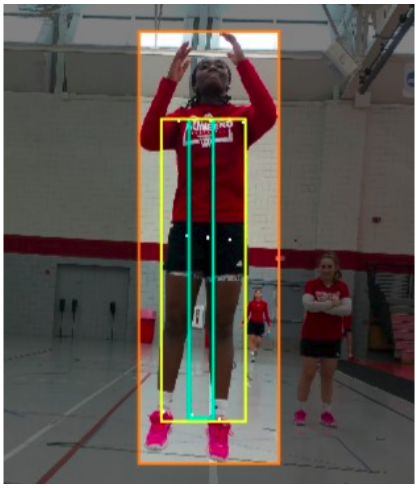

Fig. 1. Frame 51

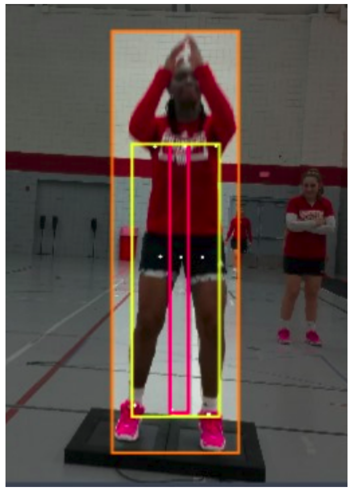

Fig. 2. Frame 52

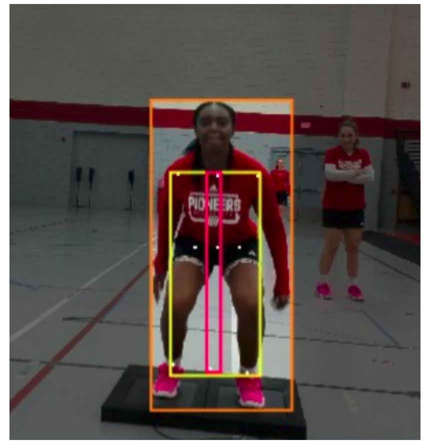

Fig. 3. Frame 54

III. RESULTS

Table I and Figures 1, 2, and 3 show the data and the results of three selected frames (Frame 51, 52, and 54).
The difference between the stance width of frame 52 and 54 is clear from the image.

IV. DISCUSSION

Having figured out the stance width and lateral flexion using the Mediapipe Pose algorithm and having labelled it with the help of Roboflow software, we now aim to develop a deep-learning model to automate the process, i.e. we will input a frame, and we hope to get the annotated image along with the labels mentioning the error if any. We would then create a visual dashboard showcasing the annotated frame with angles and distance measured. Subsequently an XAI component can be added to identify the most significant errors. This approach would help us to save time and also extend the accessibility of this process to an audience beyond athletes.

V. CONCLUSION

Lower extremity injuries severely impact athletes' performance and careers. Therefore, coaches use neuromuscular monitoring and directed training initiatives to prevent these injuries. [1] The suggested framework aids in coaches in identifying dangerous motions and improper postures. It strikes a compromise between the time-consuming and costly 3D motion analysis method and the clinician-driven screening that is hampered by intra- and inter-rater variability. Without depth, cameras or skilled doctors, automation of the LESS using familiar 2D recordings would enable mass injury-risk screening programmes with feedback in almost real-time. If this method is successfully implemented, it could automatically identify people at a high risk of injury through smartphone applications that use LESS and 2D video footage. This would increase the accessibility of injury-risk assessment methods to a broader audience than elite athletes and eliminate the need for a depth-sensor camera. [7]

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