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RESEARCH ARTICLE OPEN ACCESS

KINEMATIC ANALYSIS OF DEPTH JUMP USING COMPUTER VISION

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ABSTRACT

Currently, the analysis of the kinematics of plyometric exercises, like the depth jump, is carried out indirectly and subjectively by coaches and professionals. However, this approach has a high degree of inaccuracy, compromising the identification of technical failures and increasing the risk of injury. This paper presents an algorithm to evaluate the kinematics of deep jumping. The methodology adopted is to use the combination of computer vision techniques. This approach was validated against the Kinovea software, and the results demonstrated high precision, achieving an average angular error of less than 1.0° for the knee, hip, and ankle joints. Additionally, performance metrics such as contact time and jump height showed satisfactory consistency, proving the tool's viability for assisting coaches and athletes in optimizing performance and preventing injuries.

I. INTRODUCTION

Plyometrics is a common method for improving an athlete's Stretch-Shortening Cycle (SSC) capabilities. The term “plyometric training” is colloquially used to describe fast, powerful movements that utilize a pre-stretch, or counter-movement, and involve the SSC. Plyometrics has been commonly employed in power and speed training. Specific plyometric exercises can be used to train slow or fast RSC. Examples of slow RME plyometrics include vertical jumps and box jumps, while repeated hurdle jumps and depth jumps are typically considered fast RME movements [1]. Plyometric exercises can lead to optimization of the application of force resulting on the ground during sprinting. This is because plyometric training can improve the ability to apply the resulting force vector to the ground more effectively [2]. Among the most widely used plyometric exercises, the depth jump stands out. This movement is distinguished by the descent from a predefined height, immediately followed by an explosive rebound. The primary purpose is to minimize the period of contact with the ground and optimize the performance of the stretch-shortening cycle (SSC) during propulsion, aiming to ensure maximum performance by the athlete. One metric that can measure this performance is the Reactive Strength Index (RSI), which assesses the height of the jump in relation to the time of contact with the ground.

This metric is an indicator of the athlete's ability to quickly switch from an eccentric muscle contraction to a concentric one, functioning as a measure of “explosiveness” [1]. The integration of technology into sports training has become indispensable. As said by Niu [3], posture recognition and analysis play a crucial role in sports science, contributing to the improvement of movement technique and the prevention of injuries during practice. Related works [4-7] leverage these current technologies, employing computer vision techniques to conduct video analysis and assist in evaluating movements during specific exercises. Tools such as sensors and analysis software have been increasingly used by athletes and coaches to improve results and prevent injuries. In this context, this article proposes using computer vision and artificial intelligence to analyze the kinematics of the long jump accurately, without the use of physical markers and manual adjustments. As it is a non-invasive technique, computer vision can offer a very effective alternative to help coaches and athletes identify movements, incorrect angles, and perform technical analyses, contributing both to improving performance and preventing injuries.

The remainder of this paper is organized as follows: Section 2 presents a set of related works that point to techniques and tools that help to understand the possibilities for solving the problem. Section 3 formally presents the architecture of this work. In Section 4, the architecture is translated into a case study (software) to perform the proof of concept. In Section 5, describes the conclusion, presenting the most significant result.

II. THEORETICAL REFERENCE

The selection of related works is an important step in highlighting the relevance and soundness of a research study. For this reason, this study adopted a systematic review approach, which involves the application of a series of filters. The first filter (Filter 1) consisted of analyzing the titles and abstracts of works in Portuguese, English, and Spanish. For technologies (computer vision, AI, etc.), studies published less than five years ago were considered, while for literature and metrics (plyometrics, IFR), works published less than 20 years ago were included. The second filter (Filter 2) considered only those that addressed problems identical or similar to those proposed in this research, including the presentation of compatible methodologies and evaluation criteria. The works selected through this process are presented below.

II.1 PLYOMETRICS AND PERFORMANCE METRICS

In [8], presents a study in which he determined the influence of plyometric training on soccer goalkeepers, using several tools to measure performance metrics, such as: force platforms, dynamometers, and motion sensors. A correlation between pre- and post-tests indicated that goalkeepers with higher initial power had more significant improvements, although the training also benefited those with lower power levels. According to Juan's research[9], the objective was to determine the effects of plyometric training and average propulsive speed on the development of power in volleyball. A device called T-force was used, which can extract some data from the exercise. The author concluded that training promotes gains in the development of strength, explosive strength, and power, and that these effects impact improvements in jumping in volleyball players and also in other sports that require skills similar to volleyball.

II.2 COMPUTER VISION APPLICATIONS IN SPORTS AND HEALTH

As described in the study conducted by Valera[10], an approach is proposed in which the extraction of body measurements is performed from a simple photograph of the user, accompanied by the measurement of their height. First, the photo is processed using OpenCV. The image is read and converted to grayscale to improve performance. Next, edge detection is performed using OpenCV, through the cv2.Canny function. After this step, the MediaPipe library is used to detect the pose. This provides the information needed to calculate body measurements using NumPy. The research by Amaral[11] created an application where it was possible to track the trajectory of the bar in an Olympic weightlift (OWL) using videos recorded on a cell phone. The following libraries were used: OpenCV to process the videos and Matplotlib to plot graphs. Thus, the work was able to analyze the performance of professional and amateur weightlifters.

According to Simoes[12], a system for evaluating posture during the performance of physiotherapy exercises is presented, using real-time pose estimation. Body point detection is performed with the MediaPipe library, based on images captured by a camera. The extracted information is The extracted information is processed to identify repetitions and classify movements using machine learning techniques such as KNN and Naïve Bayes. The system achieved an average accuracy of 99.22% in the analysis of upper limb movements, demonstrating its potential as a computational tool to support home-based physical rehabilitation. To facilitate the visualization of different approaches found in the literature, Table 1 summarizes the main characteristics of the related works. The comparison shows the technologies used to solve similar problems and illustrates the common points between these studies and the current work.

Table 1: Related studies.

Author(s)	OpenCV	Mediapipe	Numpy	Matplotlib	Machine Learning Algorithms	External Sensors
Ballagan, 2024 [8]						X
Juan, 2022 [9]						X
Valera, 2024 [10]	X	X	X			
Amaral, 2023 [11]	X			X		
Simoes, 2024 [12]		X			X	
This Study	X	X	X	X		

Source: Authors, (2025).

The choice of this methodology in our work, with an emphasis on computer vision, is justified by its ability to provide a detailed kinematic analysis in a non-invasive, accessible way (using conventional cameras). The combination of pose detection via MediaPipe with kinematic calculations in Python allows for a solution without the need for physical markers, overcoming the limitations of subjective observation and the invasiveness of some sensors. The computer vision approach, unlike sensor-based solutions, offers the benefit of recording the complete visual context of movement, which is valuable for qualitative analysis by coaches. The technological decisions made here, based on this analysis of pros and cons, are presented in architectural format in Section 3.

III. MATERIALS AND METHODS

This section describes the proposed method for developing the application for analyzing the kinematics of the depth jump, using a computer vision-based approach. The process was organized into sequential steps, as illustrated in the block diagram in Figure 1.

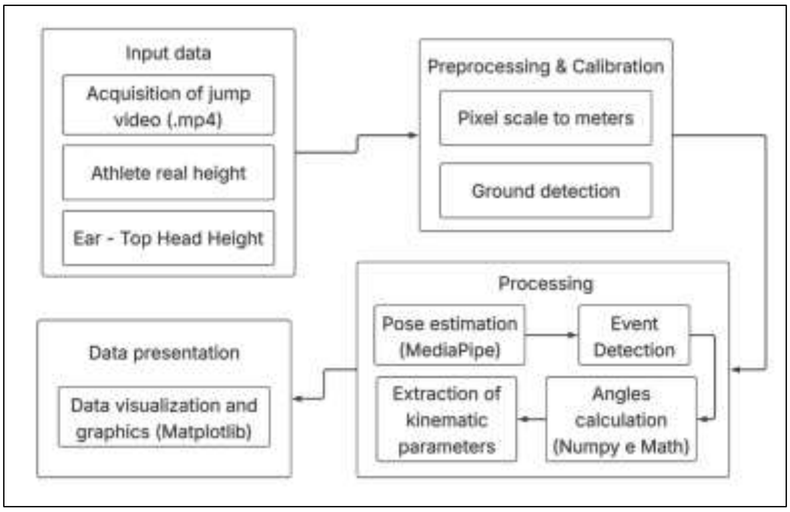


Figure 1: Block Diagram.
Source: Authors, (2025).

III.1 INPUT DATA

The process begins with the collection of video footage featuring athletes from various sports and contexts. These recordings are captured using standard cameras or mobile devices, with a strict emphasis on a side-profile view that encompasses the athlete's entire body to ensure precise kinematic analysis as shown in Figure 2.

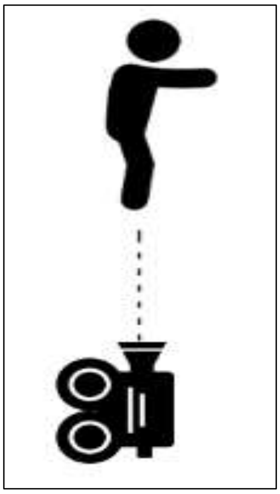


Figure 2: Camera positioned to the side of the athlete to record the jump.
Source: Authors, (2025).

Beyond the video, the system requires specific anthropometric data for calibration. The athlete's actual height (in meters) is the primary input, allowing the software to translate pixel data into real-world metric units. To further refine this accuracy, the vertical offset between the ear and the top of the head is also incorporated. This auxiliary measurement is crucial because the ear landmark detected by MediaPipe offers a significantly more stable reference point than the top of the head for estimating total body stature.

III.2 PREPROCESSING & CALIBRATION

Prior to executing the core kinematic analysis, the system undergoes a necessary preprocessing and calibration stage. This phase is dedicated to defining two critical spatial baselines: the precise ground level and the metric conversion scale.

- Ground Detection: Initially, the algorithm executes a preliminary scan of the entire video footage. By leveraging the MediaPipe model, it tracks the vertical position (Y-axis) of the foot landmarks(specifically the heel and big toe) across every frame. The algorithm isolates the highest Y-value detected during the sequence (which corresponds to the lowest physical point in the image) and establishes this as the fixed ground coordinate, this baseline is a prerequisite for the Height and Contact time.

- Pixel Scale to Meters (Scale Calibration): Following ground detection, the system calibrates the scale during the initial frames of the main analysis pass. Here, the system synthesizes the input data regarding the athlete’s actual height with the auxiliary 'Ear-to-Top-of-Head' offset. By measuring the pixel distance between the ear and heel landmarks and adjusting for the head offset, the software estimates the athlete's full height in digital terms. Comparing this pixel count against the athlete's real-world height in meters allows the system to derive a precise conversion ratio. This ratio is then applied to translate all subsequent pixel-based measurements, such as jump height, into accurate metric units.

III.3 PROCESSING

III.3.1 Body Detection and Tracking (Pose Estimation)

A model based on Pose Estimation will be used to identify and track points on the athlete's body. This will allow the movement and angles of the joints to be mapped, thus creating a biomechanical model of the athlete. A Pose Estimation algorithm from the MediaPipe library will be used, which is responsible for automatically identifying and tracking the joint points (Landmarks) of the athlete's body, as illustrated in Figure 3. This detection will allow the Analysis of movement and the calculation of the kinematic parameters.

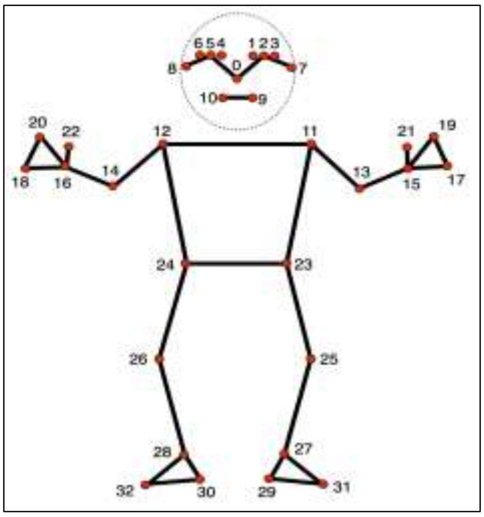


Figure 3: Mediapipe Landmarks.
Source: Authors, (2025).

III.3.2 Kinematic Parameters and Angles Calculation

Based on the location of the landmarks extracted using the Pose Estimation model from the MediaPipe library, calculations are performed with the support of the NumPy and Math libraries. These calculations aim to identify the following kinematic parameters that describe the execution and performance of the depth jump:

- Knee angle: calculated from the hip, knee, and ankle landmarks .
- Hip angle: calculated from the shoulder, hip, and knee landmarks.
- Ankle angle: calculated from the knee, ankle, and an imaginary point that runs parallel to the movement of the foot.
- Ground contact time: interval between the moment the feet touch the ground and the moment they leave the ground again.
- Jump height: calculated from the lowest point of the foot, the highest point of the foot, and the athlete's height for comparison.
- Reactive Strength Index (RSI): the ratio between jump height and ground contact time.

These parameters will enable a detailed kinematic analysis of the athlete's performance, allowing the identification of technical patterns or functional deficits, with direct application in physical assessment and injury prevention contexts.

III.4 DATA VISUALIZATION

The presentation of the system data is divided into two main outputs, both crucial for analysis:

- Real-time Annotated Video: During the processing phase, the system generates two simultaneous viewing windows. The first window displays the original video with an overlay of data, such as the pose estimation and angle values. The second window displays only the pose estimation and analysis information (angles, height lines, contact status) on a black background. This separation “cleans” the visual environment, removing the distraction of the original video and making landmarks, angles, and metrics significantly more visible to the analyst.

- Post-processing Graphics: After complete analysis of the video, the extracted data (time series of angles, contact events) are used to generate static graphical visualizations with the Matplotlib library. These graphs allow for detailed analysis of parameter variation over time. In addition, calculated performance indices, such as the RSI (Reactive Strength Index), are displayed on the console.

IV. RESULTS AND DISCUSSIONS

This chapter presents the results of the algorithm's development and the technical validation of the values obtained by the Proof of Concept (POC).

IV.1 OVERVIEW OF THE PROPOSED SOLUTION

The developed computer vision system is designed to process depth jump footage, delivering immediate visual and metric feedback. To enhance the interpretability of the kinematic parameters in real-time, the output interface is split into two distinct windows. The figure 4 illustrates the initial frames within the main window, highlighting the estimation of the subject's total height

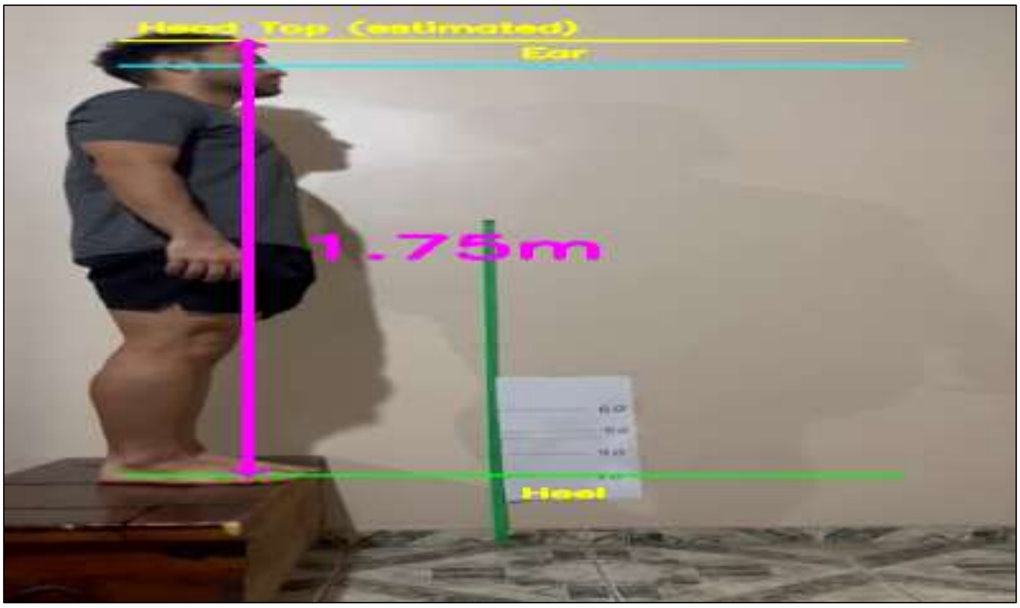


Figure 4: First frames.
Source: Authors, (2025).

Figure 5 depicts the system's output during the critical landing phase. The display presents two simultaneous perspectives generated by the algorithm: on the left, the view isolates body segments against a black background. This design choice eliminates environmental visual noise, ensuring a clean and precise reading of the angular geometry at the moment of impact. On the right side, the main window overlays this data directly onto the original video feed, demonstrating the precise alignment of the pose estimation model with the athlete's physical posture.

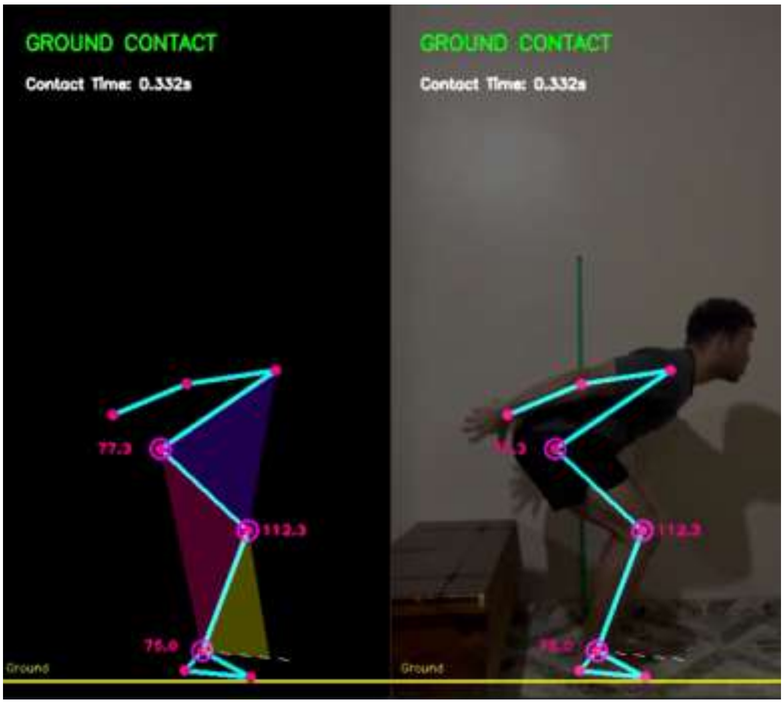


Figure 5: Windows with landmarks and angles.
Source: Authors, (2025).

Figure 6 demonstrates the system's capability to track the jump's aerial component. The transition is triggered the moment the foot landmarks rise above the defined ground tolerance, prompting the status indicator to switch to a red 'IN AIR' signal. Throughout this phase, the algorithm monitors the foot's vertical displacement, projecting a green reference line at the peak to measure the distance relative to the yellow ground baseline. By applying the pixel-to-meter calibration factor in real-time, the system renders the final height directly on the screen, providing the evaluator with immediate feedback on the athlete's vertical performance.

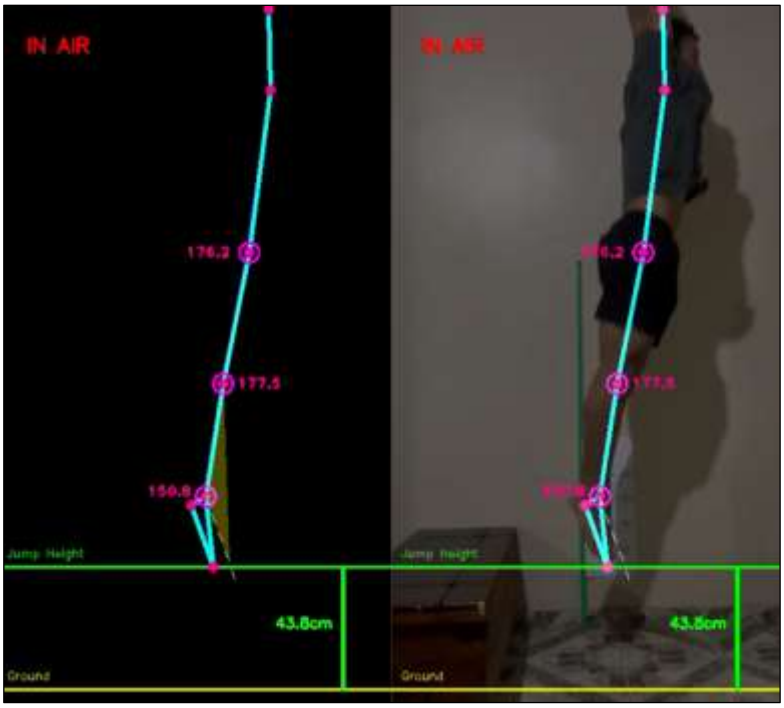


Figure 6: Windows with landmarks and angles.
Source: Authors, (2025).

After processing the video, the system automatically generates graphical reports for detailed analysis of depth jump and information at the terminal, as illustrated in Figure 7 and Figure 8.

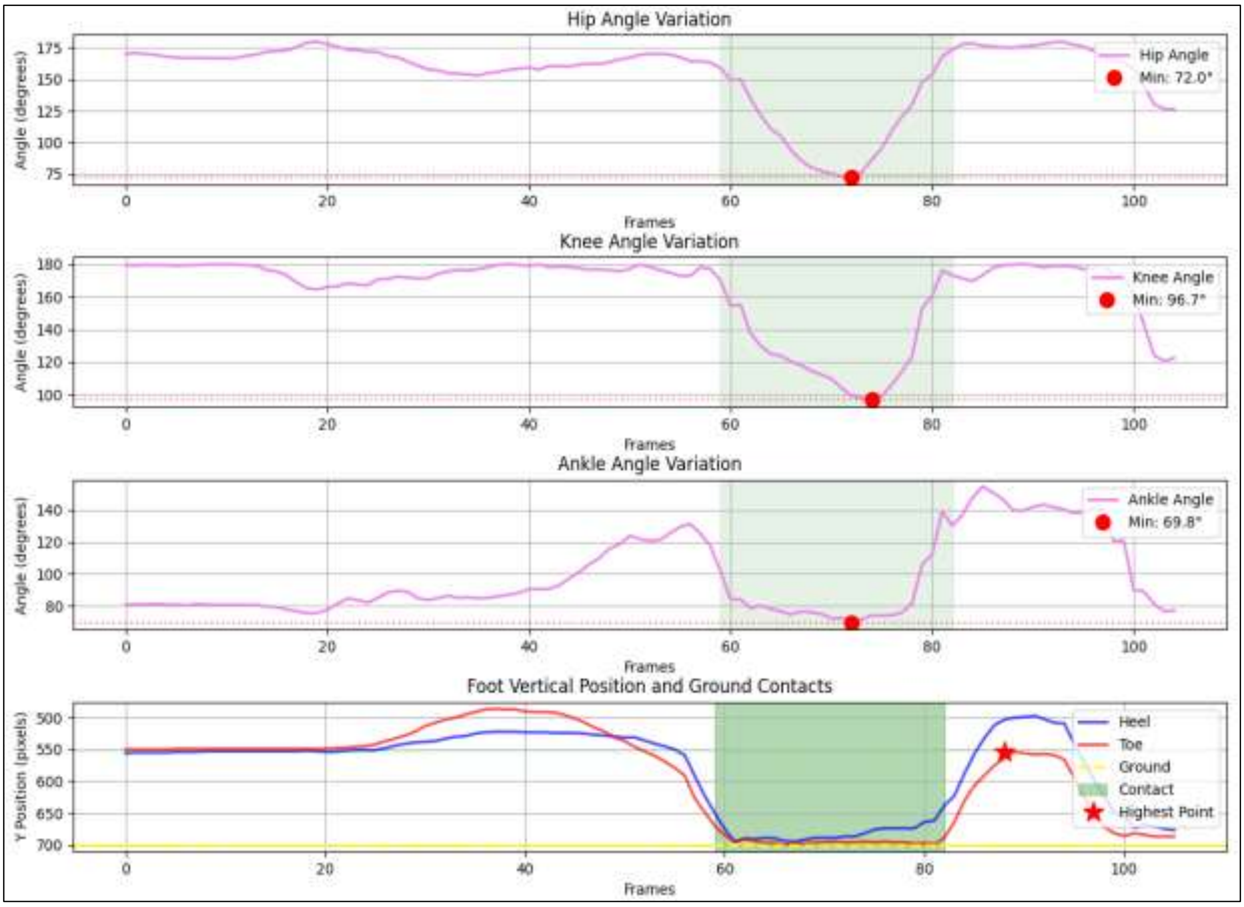
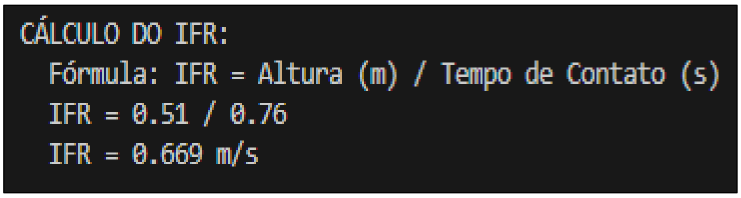


Figure 7: Time series showing the angular variation and vertical position of the foot over time.
Source: Authors, (2025).



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CÁLCULO DO IFR:
  Fórmula: IFR = Altura (m) / Tempo de Contato (s)
  IFR = 0.51 / 0.76
  IFR = 0.669 m/s
```

Figure 8: Calculation of the IFR at the Terminal.
Source: Authors, (2025).

IV.2 TECHNICAL VALIDATION OF PARAMETERS

To demonstrate the accuracy of the data displayed by the system, a validation was performed using a set of 3 depth jump videos (N=3). The comparison was using Kinovea software and manual analysis:

- Kinovea: Used to measure joint angles and contact time (frame counting).
- Manual Analysis: Used for Jump Height, using an auxiliary camera and inspection with zoom on the reference tape measure.

IV.2.1 Kinematic Parameters and Angles Calculation

Figure 9 shows the use of Kinovea, software used by coaches of various sports to assist in the analysis of exercise movements or in a particular sport. In the software, it is possible to add angles, but manual adjustments are necessary to position the points. These angles are seen in the image as blue arcs in the right window.

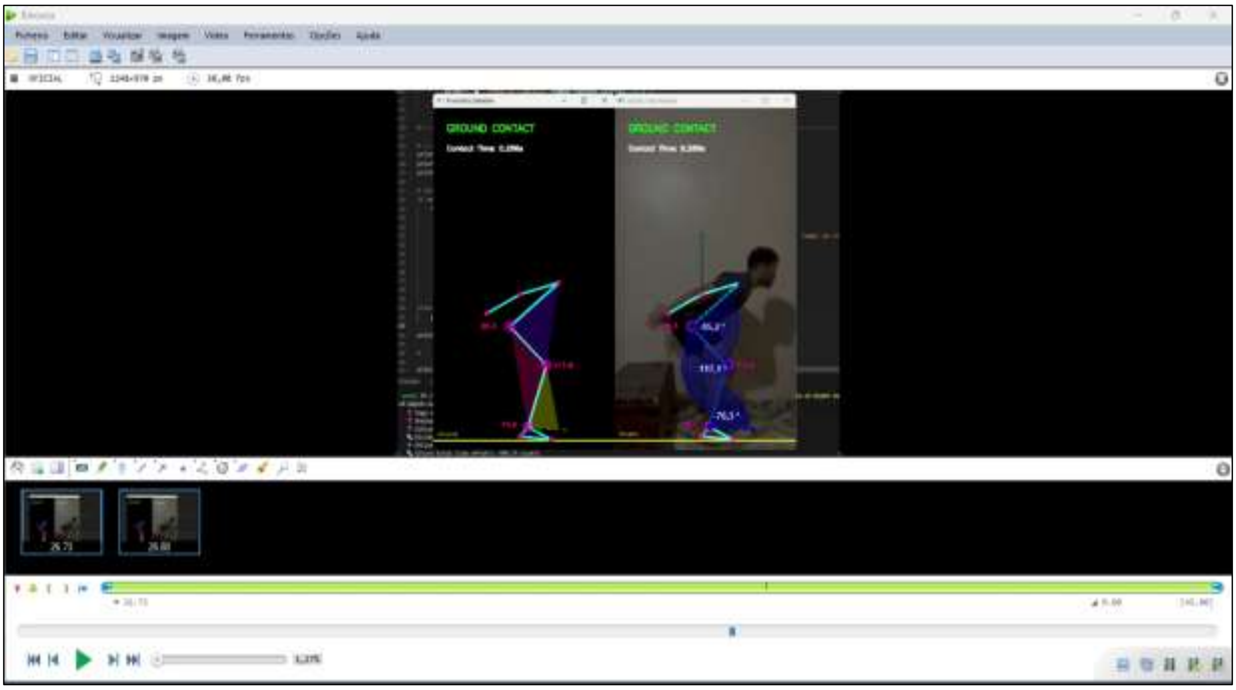

Figure 9: Use of Kinovea software to compare angulation.
Source: Authors, (2025).

IV.2.2 Jump height

Validating the jump height through manual analysis presented challenges inherent to video capture. The main obstacle identified was the parallax error caused by the difference in depth between the capture planes:

- Reference Plane: The measuring tape fixed to the wall (background).
- Movement Plane: The athlete performing the jump positioned in front of the wall (foreground).

The lateral camera perspective introduced a parallax error due to the gap between the athlete in the foreground and the wall tape measure. This depth difference created visual distortion, complicating the precise reading of the jump's peak. To counter this, we utilized a low angle auxiliary camera positioned near the ground to minimize the angle of incidence, facilitating a direct alignment verification between the heel and the metric scale (as shown in Figure 10). However, given the inherent depth limitations, a tolerance margin of ± 5 cm was applied to the manual reference values. Consequently, minor discrepancies falling within this range are attributed to the physical challenges of manual measurement rather than solely to algorithmic inaccuracies

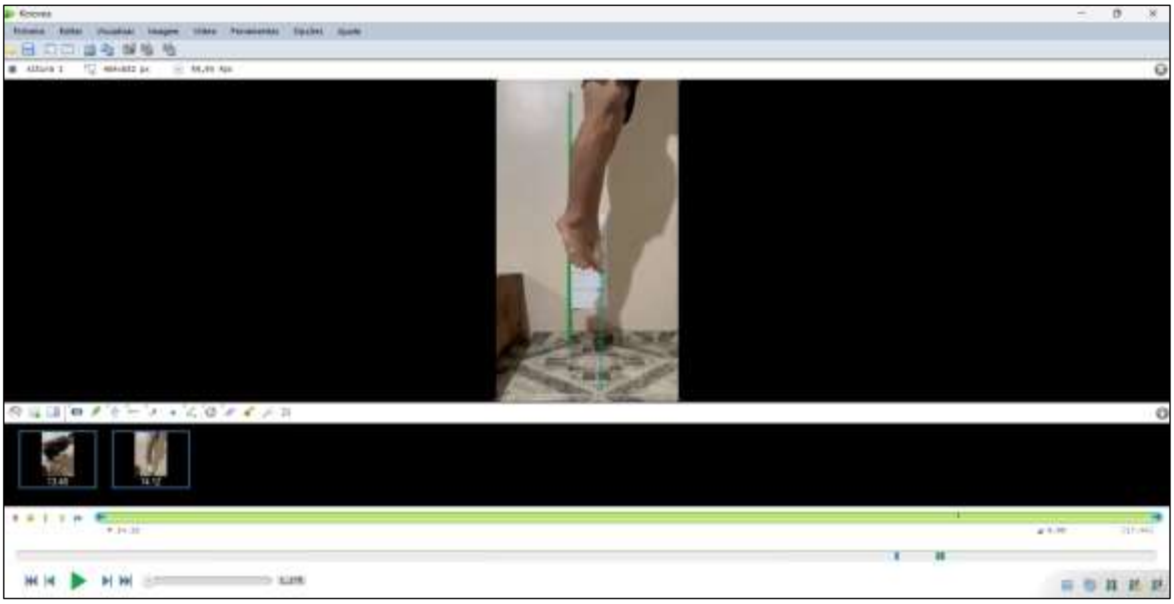

Figure 10: Use of Kinovea software for height analysis.
Source: Authors, (2025).

IV.2.3 Contact time

Kinovea software was used to validate contact time, the procedure consisted of a frame-by-frame visual analysis to isolate two events and total contact time was obtained by calculating the time difference between these two events. Figure 11 illustrates the frame identified as the initial contact.

- Initial Contact: The first frame in which any part of the foot touches the ground.
- Toe off: The last frame immediately before the foot completely loses contact with the surface.

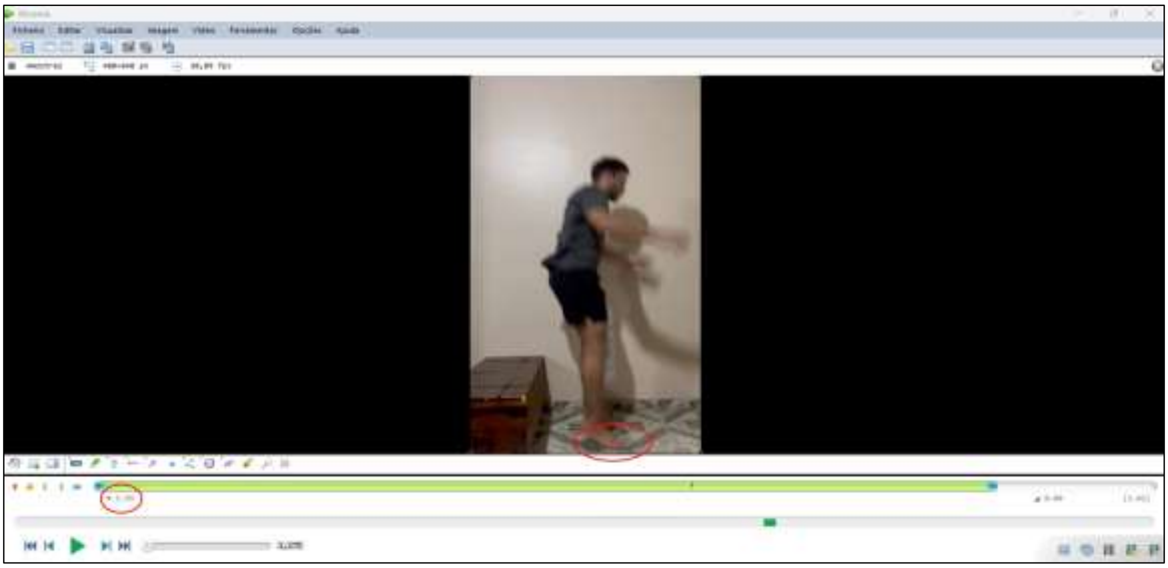

Figure 11: Use of Kinovea software for contact time analysis.
Source: Authors, (2025).

IV.2.4 Sample Results

Tables 2, 3, and 4 show the data collected from the three samples and consolidate the direct comparison between the Kinovea values and the values calculated by the algorithm.

Table 2: Comparison of Kinematic Parameters for Sample 1.

Parameter	Unit	Kinovea/Manual	Algorithm(Mediapipe)	Difference (Error)
Hip Angle	Degrees (°)	85,2°	85,5°	0,3°
Knee Angle	Degrees (°)	117,1°	117,8°	0,7°
Ankle Angle	Degrees (°)	76,3°	76,6°	0,3°
Contact Time	Seconds (s)	0.72 s	0.76 s	0.04 s
Jump Height	Centimeters (cm)	+/- 47	51	+/- 4

Source: Authors, (2025).

Table 3: Comparison of Kinematic Parameters for Sample 2.

Parameter	Unit	Kinovea/Manual	Algorithm (Mediapipe)	Difference (Error)
Hip Angle	Degrees (°)	93,3°	93,3°	0°
Knee Angle	Degrees (°)	116,1°	116,5°	0,4°
Ankle Angle	Degrees (°)	79,2°	79,9°	0,7°
Contact Time	Seconds (s)	0.67 s	0.66 s	0.01 s
Jump Height	Centimeters (cm)	+/- 35	39	+/- 4

Source: Authors, (2025).

Table 4: Comparison of Kinematic Parameters for Sample 3

Parameter	Unit	Kinovea/Manual	Algorithm (Mediapipe)	Difference (Error)
Hip Angle	Degrees (°)	71,5°	71,3°	0,2°
Knee Angle	Degrees (°)	99,2°	99,1°	0,1°
Ankle Angle	Degrees (°)	67,9°	68,2°	0,3°
Contact Time	Seconds (s)	0.73 s	0.65 s	0.08 s
Jump Height	Centimeters (cm)	+/- 44	49	+/- 5

Source: Authors, (2025).

V. CONCLUSIONS

Kinematic analysis of depth jumps is a fundamental tool to evaluate reactive strength and prevent injuries, but its practical application is often restricted by the high cost and complexity of laboratory equipment, such as force platforms. This study addressed this gap by developing a Proof of Concept (POC) based on Computer Vision. The main objective was to demonstrate that it is possible to extract biomechanical metrics without markers (non-invasive) and in an accessible way, only with a conventional camera. The results obtained in the validation confirm the practicability and feasibility of the proposed system. Compared to Kinovea, the algorithm demonstrated excellence in angles analysis, achieving angular accuracy with an average error of less than 1.0° for the knee, hip, and ankle joints. Performance metrics, such as contact time and jump height, showed satisfactory consistency for field applications, validating the algorithm's ability to calculate the Reactive Strength Index (RSI) and provide immediate visual feedback on landing technique.

The solution's strengths include portability, low implementation cost, and the elimination of the need to prepare athletes with physical markers, facilitating its adoption in real training environments. However, the POC revealed limitations, specifically parallax error, which introduces deviations in the absolute measurement of height depending on the athlete's depth and dependence on the camera's frame rate(FPS) , which imposes a limit on the temporal resolution of contact detection. For future work, we suggest using high-speed cameras (>120 FPS) to refine the accuracy of contact time and depth sensors to mitigate parallax errors. The addition of a frontal or diagonal view, simultaneous with the lateral view, would allow the analysis of knee or foot symmetry, thus identifying injury risks and enabling a more detailed assessment of landing mechanics. Finally, the development of a Graphical User Interface (GUI) would be the next step to transform this prototype into a final product for use by coaches and athletes.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Augusto César Silvestre da Silva, Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio
Methodology: Augusto César Silvestre da Silva, Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio
Investigation: Augusto César Silvestre da Silva, Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio
Discussion of results: Augusto César Silvestre da Silva, Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio
Writing – Original Draft: Augusto César Silvestre da Silva, Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio
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Resources: Augusto César Silvestre da Silva, Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio
Supervision: Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio
Approval of the final text: Walter Charles Sousa Seiffert Simoes, Lucas Tavares Sampaio

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