# Assessment of Athletic Readiness Using Countermovement Jump Videos

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***Abstract*—Collegiate basketball demands not only peak physical performance but also swift recovery from fatigue, making continuous monitoring of athletic readiness essential. In this study, we introduce a novel, non-invasive framework that leverages video analysis of Countermovement Jumps (CMJs) to assess readiness in 17 female athletes. High-definition videos recorded at 30 frames per second are processed with MediaPipe for real-time pose estimation, extracting key biomechanical metrics such as jump height, power output, flight time, and phase durations. These metrics are integrated into a machine learning model that predicts readiness states—ranging from optimal performance to signs of fatigue. Our results demonstrate that this cost-effective and scalable approach not only correlates well with traditional force plate measurements but also provides coaches with actionable insights for adjusting training and recovery protocols. Overall, the framework bridges advanced computer vision techniques and sports science, highlighting its potential for widespread application in athletic performance monitoring.**

***Index Terms*—Athletic readiness, Biomechanics, Collegiate basketball, Computer vision, Countermovement jump, Performance metrics, Video analysis**

## I. Introduction

Collegiate basketball places significant physical and mental demands on athletes, compounded by academic responsibilities and frequent games. Monitoring athletic readiness—defined as an athlete's capacity to perform optimally while minimizing injury risk—is thus essential for maintaining performance and well-being. Traditionally, readiness has been assessed using tools like force plates to analyze Countermovement Jumps (CMJs), a widely accepted measure of lower-body power and fatigue. However, these methods are costly, require specialized equipment, and involve time-intensive data processing, limiting their practicality for regular use in collegiate settings.

This study introduces a novel approach: using video analysis to monitor CMJs and extract key performance indicators (KPIs) for predicting readiness. By employing accessible camera technology and computer vision, we aim to overcome the limitations of traditional methods, offering a scalable and efficient alternative. The significance of this research lies in its potential to provide coaches with actionable insights into athlete readiness, enabling data-driven adjustments to training and recovery protocols. This paper outlines our methodology, presents initial findings, and discusses the implications for sports science and collegiate basketball.

## II. Methodology

Seventeen female collegiate basketball athletes of Sacred Heart University (SHU), CT, USA, participated in weekly CMJs over a 26-week season. [1]Through CV-driven semantic analysis of videos, the framework identifies the crucial initial contact and maximum flexion point during jump landings and extracts kinetic and kinematic features of the lower extremities.

Participants performed CMJs following a standardized protocol: Jumps were filmed using a high-definition camera, positioned to capture full-body motion. MediaPipe was employed for real-time pose estimation(30 frames per second), tracking key anatomical points (e.g., hips, knees, ankles).

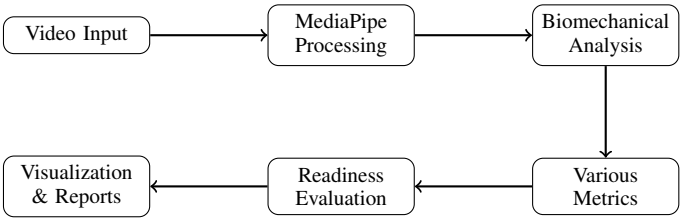


**Fig. 1:** Proposed Workflow

### A. Video Input

The process begins with recording a CMJ at 30 fps to capture full-body motion and all key jump phases. This raw video data forms the basis for the entire analysis.

### B. MediaPipe Processing

MediaPipe [2] extracts key anatomical landmarks by tracking joints frame-by-frame. It converts raw footage into structured data for further analysis.

### C. Biomechanical Analysis

Extracted keypoints are analyzed to compute metrics like jump height, maximum velocity, and phase durations. This analysis transforms raw data into actionable performance insights.

### D. Various Metrics

Computed metrics, including readiness scores and symmetry indices, quantify the athlete's performance state. These metrics guide coaches in evaluating and adjusting training protocols.

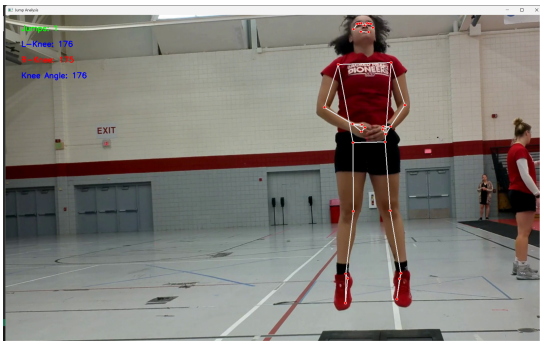


**Fig. 2:** Metrics capturing during CMJ

| Metric Name | Basic Explanation |
|---|---|
| Power Output [3] | Measures explosive strength |
| Eccentric Phase Duration [4] | Time for downward movement |
| Concentric Phase Duration | Time for upward movement |
| Max Velocity During Jump [5] | Peak center of mass speed |
| Symmetry Indices for Joints [6] | Balance between left and right |

**TABLE I**
New Discovered Jump Performance Metrics

### *E. Readiness Evaluation*

Extracted biomechanical metrics are input into a machine learning model to classify athletes as "Ready" or "Fatigued." The model analyzes movement patterns, with lower jump height or power output indicating fatigue. This approach enables real-time assessment for training adjustments.

### *F. Visualization & Reports*

Results are presented via graphs and dashboards, showing trends in jump metrics and readiness scores. Coaches can use these insights to adjust training loads and recovery strategies effectively.

## III. Observations and Discussion

The CMJ-derived biomechanical metrics align with expected thresholds for trained athletes, validating their use in readiness evaluation.

**Jump Height (m):** 0.30–0.40, **Power Output (W):** 20–25, **Flight Time (s):** 1.0–1.2, **Eccentric Duration (s):** 0.1–0.2, **Concentric Duration (s):** 0.20–0.35, **Max Velocity (m/s):** 1.5–2,**Symmetry Index:** 0.1–0.2

***Experimental Results:***

```
{'Jump': 1, 'Jump Height (m)': 0.296, 'Power
    Output (W)': 18.98,
 'Flight Time (s)': 10.7, 'Eccentric Duration
     (s)': 0.028,
 'Concentric Duration (s)': 0.329, 'Max
     Velocity (m/s)': 1.409,
 'Symmetry Index': 0.288}
```

Our initial analysis indicates that while some metrics, like jump height and power output, align with expected thresholds, others, such as phase durations, require further refinement. This variability suggests the need for improved detection methods to better capture subtle biomechanical differences. Integrating these metrics into a machine learning model provides a foundation for readiness evaluation, but additional validation is needed to enhance accuracy and robustness.

## IV. Conclusion

This paper has presented a connected framework that integrates video-based analysis, advanced pose estimation, and machine learning to assess athletic readiness in collegiate basketball. By extracting detailed biomechanical metrics from CMJ videos, our approach offers a practical alternative to conventional, equipment-intensive methods. The experimental results validate that key performance indicators—such as jump height, power output, and phase durations—are effective in discerning readiness states, thereby enabling timely adjustments in training and recovery strategies. Moving forward, further refinements in model accuracy and broader validation across diverse athlete groups will strengthen the framework's applicability. Ultimately, this work bridges the gap between innovative computer vision techniques and real-world sports science, paving the way for more data-driven and responsive athletic performance monitoring.

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