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# Computer Vision for Biomechanical Analysis in Cricket: A Survey of Techniques, Challenges, and Future Directions

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***Abstract*—Using quantitative methods to analyze sports biomechanics is now essential for enhancing athletic output and reducing injury potential. For a sport like cricket, which is defined by intricate and rapid movements, the need for scalable and objective analytical tools is especially high. This paper delivers a thorough review of current computer vision and machine learning applications within cricket's biomechanical analysis, concentrating specifically on batting. We offer a formal classification of the current body of work, organizing studies by their primary objectives, such as correcting technique, analyzing performance, or predicting injury. This review also charts a clear technological progression, detailing the field's shift from intrusive, wearable sensors to non-invasive, vision-based systems driven by deep learning and pose estimation. The dominant methodologies are critically evaluated, along with their respective contributions and inherent drawbacks. From this analysis, we pinpoint key trends and persistent obstacles—like model generalizability and a scarcity of high-quality data—as well as promising avenues for future work, including 3D pose modeling, multi-modal sensor fusion, and Explainable AI (XAI). This survey acts as a foundational reference for academics and industry professionals, offering a systematic overview of the discipline and pinpointing open questions for further research.**

***Keywords*—Survey, Cricket Biomechanics, Pose Estimation, Computer Vision, Injury Prevention, Machine Learning, Sports Analytics, Literature Review.**

## I. INTRODUCTION

Cricket is a sport where technical proficiency, underpinned by sound biomechanics, is a fundamental determinant of success and athletic longevity. The actions of batting and bowling involve complex, high-velocity kinetic chains where minor technical flaws, if left uncorrected, can accumulate to cause career-limiting injuries [6]. For decades, the analysis of these movements has been the domain of expert coaches, whose subjective assessments have been the cornerstone of player development. However, the increasing physical demands of the modern game have necessitated a shift towards more objective, quantitative, and data-driven methods of analysis.

The initial wave of technological intervention in cricket analytics was led by wearable technologies, such as inertial measurement units (IMUs), which provided the first quantitative insights into player kinematics and workload [7]. While trans-formative, these sensor-based approaches have practical limitations, including their intrusive nature and high cost. The last decade has witnessed a paradigm shift, driven by significant advancements in computer vision and deep learning. As a non-invasive substitute for traditional, sensor-based techniques, markerless human pose estimation has become a prominent and powerful tool, capable of extracting high-fidelity skeletal data from standard video footage [2]. This has democratized sports science, enabling sophisticated biomechanical analysis outside the confines of expensive laboratories.

As the volume of research in this domain accelerates, a clear and consolidated overview of the field is needed. Numerous studies have focused on specific applications, such as shot classification or benchmarking pose estimation models [3], but a holistic survey that organizes these efforts, identifies overarching trends, and outlines future challenges is lacking. This paper aims to fill that gap. We provide a comprehensive survey of machine learning and computer vision techniques for biomechanical analysis in cricket, with a primary focus on batting. We present a structured review of the key literature, analyze the evolution of methodologies, and synthesize the primary challenges and opportunities. The contribution of the paper is a clear taxonomy of the current research landscape, which serves as a guide for future work aimed at developing the next generation of intelligent systems for cricket analytics.

## II. SURVEY OF THE LITERATURE

To provide a structured overview, we have categorized the relevant literature based on the primary techniques and applications. We analyze each work's objective, methodology, and key contributions.

### A. *Vision-Based Pose Estimation and Action Recognition*

1) Toward Real-Time Recognition of Continuous Indian Sign Language (2023) [1]:
   - Objective: A real-time recognition framework, Sign- Flow, was developed for continuous Indian Sign Lan- guage (ISL), including the creation of the first bench- mark ISL dataset and a deployable chatbot system.
   - Methods: A hybrid 3DResNet and 8-layer Transformer model was implemented with a domain-specific pre- training strategy. The model was fine-tuned using CTC loss and optimized for real-time inference through a dynamic 6 fps down-sampling pipeline.
   - Results and Key Contribution: SignFlow established the first real-time ISL framework and dataset, achieving a Word Error Rate (WER) of 19. This work showcases the power of multi-modal deep learning for real-time human action recognition, with principles generalizable to sports analysis.
2) Motion Capturing in Cricket: Comparison of Medi- aPipe and OpenPose (2024) [3]:
   - Objective: To benchmark the performance of two leading markerless pose estimation frameworks, Me- diaPipe and OpenPose, specifically for cricket-related movements.
   - Methods: Conducted a comparative analysis of the accuracy and processing speed of both frameworks on a custom dataset of cricket actions.
   - Results and Key Contribution: The study quantita- tively confirmed the well-known speed-accuracy trade- off: OpenPose delivered higher accuracy, while Medi- aPipe offered significantly faster real-time performance. This provides a crucial guideline for selecting the right tool for a given application.
3) Enhancing Cricket Performance Analysis with Hu- man Pose Estimation and ML (2023) [2]:
   - Objective: To automate the classification of different cricket batting strokes using pose estimation and ma- chine learning.
   - Methods: Used the MediaPipe framework to extract pose data from video and fed these features into an ML model to classify eight distinct types of batting strokes.
   - Results and Key Contribution: The system demon- strated high accuracy in stroke classification, proving the viability of pose estimation for fine-grained action recognition in cricket. Its main limitation is its narrow focus on shot classification rather than holistic postural analysis and injury risk.
4) Automated Recognition of Cricket Batting Backlift Technique Using Deep Learning (2022) [4]:
   - Objective: To develop an automated system for recog- nizing different cricket batting backlift techniques using deep learning approaches.
   - Methods: Implemented deep learning models for ana- lyzing video footage to classify backlift variations.
   - Results and Key Contribution: Successfully demon- strated automated recognition of backlift techniques, providing coaches with objective assessment tools.
5) Deep Learning for Pose Estimation in Cricket: Ad- vances and Applications (2023) [8]:
   - Objective: To offer a detailed survey of existing deep learning (DL) methodologies, specifically as they are applied to pose estimation within the domain of cricket.
   - Methods: The authors conduct a systematic examina- tion of diverse deep learning architectures, encompass- ing CNNs, RNNs, and Transformers, to assess their suitability for various pose estimation tasks.
   - Results and Key Contribution: The study successfully pinpointed the most effective

network architectures for a range of cricket-specific applications. Furthermore, it underscored the critical need for temporal modeling to accurately analyze dynamic motion.

6) 3D Human Pose Estimation from a Single Image: Applications in Sports Analytics (2023) [19]:
   - Objective: To develop methods for extracting 3D pose information from single 2D images for sports applications.
   - Methods: To achieve 3D pose estimation from a single camera view, the paper's methodology applied deep neural networks. These networks were guided by geo- metric constraints to accurately "lift" the 2D pose data into a 3D representation.
   - Results and Key Contribution: Demonstrated feasibility of single-camera 3D pose estimation with ap- plications to cricket batting analysis, though accuracy remains limited compared to multi-view approaches.
7) Automated Video Analysis for Technique Correction in Batting Sports (2022) [21]:
   - Objective: To develop automated systems for identify- ing and correcting technical flaws in batting techniques across different sports.
   - Methods: Combined pose estimation with biomechanical models to detect deviations from optimal technique patterns.
   - Results and Key Contribution: Successfully identified common technical errors and provided automated corrective feedback, though generalization across different skill levels remained challenging.

*B. Injury Prediction and Biomechanical Analysis*

8) Injury Prediction and Prevention for Cricket Players Using AI (2025) [13]:
   - Objective: To develop an AI-driven system using wear- able sensor data to predict and prevent injuries in cricket players by analyzing biomechanics, workload, and fatigue.
   - Methods: The study utilized a range of Machine Learn- ing models (Random Forest, SVM, DNN) that were trained on a dataset collected directly from IMU sensors attached to the players..
   - Results and Key Contribution: The system success- fully provided real-time injury alerts and personalized training recommendations. Its primary contribution is a proactive, sensor-based injury prevention framework, though its accuracy is highly dependent on sensor fidelity and can intrusive.
9) ML-Based Pattern Recognition of Risk Factors for Low Back Pain in Adolescent Cricket Players (2025) [14]:
   - Objective: To utilize machine learning for the purpose of detecting biomechanical risk factors that lead to low back pain in junior cricket players.
   - Results and Key Contribution: Identified key move- ment patterns associated with the increased injury risk, enabling early intervention strategies.
10) New Zealand Cricket Injury Analysis (2005–2016): A Retrospective Study (2022) [5]:
    - Objective: To analyze injury patterns and trends in New Zealand cricket over an 11-year period.
    - Methods: Retrospective analysis of injury data using statistical methods to identify patterns and risk factors.
    - Results and Key Contribution: Established baseline injury rates and identified high-risk periods and player demographics, providing essential data for developing targeted prevention strategies.

11) Injuries in Cricket: A Clinical Review of Epidemiol- ogy and Management (2017) [6]:
    - Objective: To provide a comprehensive clinical review of cricket injuries, their epidemiology, and management strategies.
    - Methods: Systematic review of clinical studies and injury databases to establish injury patterns and best practices for management.
    - Results and Key Contribution: Created a comprehen- sive framework for understanding cricket injuries, es- tablishing the foundation for technology-assisted injury prevention systems.

12) Biomechanical Predictors of Injury in Elite Cricket Players: A Longitudinal Study (2023) [10]:
    - Objective: To identify specific biomechanical markers that predict injury risk in elite cricket players through longitudinal monitoring.
    - Methods: Conducted a multi-year study

tracking biomechanical variables and injury outcomes in pro- fessional cricketers.
- Results and Key Contribution: Identified key biomechanical predictors including asymmetry in movement patterns and specific joint loading profiles that precede injury onset.

13) Injury Mechanism Analysis in Fast Bowling: A Biome- chanical Perspective (2022) [12]:
    - Objective: For analyze the biomechanical mechanisms underlying common injuries in fast bowling.
    - Methods: Combined high-speed video analysis with biomechanical modeling to understand injury mecha- nisms.
    - Results and Key Contribution: Provided detailed insights into the kinetic chain disruptions that lead to injuries, informing both prevention strategies and technique modifications.
14) Assessment of ACL Injury Risk in Cricket via Key Point Detection (2023) [18]:
    - Objective: To build a computer vision framework ca- pable of evaluating ACL injury susceptibility in cricket players, based on an analysis of knee valgus angles during the landing phase.
    - Methods: Used key point detection algorithms to track knee and hip positions during dynamic movements.
    - Results and Key Contribution: The system's ability to identify specific, high-risk movement patterns asso- ciated with ACL injuries allows for the implementation of focused interventions aimed at prevention.
15) Data Analytics in Injury Prevention in Cricket: A Review of Modern Approaches (2023) [23]:
    - Objective: To review modern data analytics approaches for injury prevention in cricket.
    - Methods: Systematic review of data-driven injury prevention methods including predictive modeling and risk stratification.
    - Results and Key Contribution: Identified best practices for implementing data analytics in cricket injury prevention programs and highlighted the importance of integrating multiple data sources.

*C. Sensor-Based and Multi-Modal Approaches*

16) Advanced Kinematic Analysis of Cricket Bowlers Using Wearable Sensors and Machine Learning (2024) [15]:
    - Objective: To perform detailed kinematic analysis of bowling actions using sensor-based approaches.
    - Methods: Combined wearable sensor data with ma- chine learning algorithms for comprehensive movement analysis.
    - Results and Key Contribution: Provided detailed insights into bowling biomechanics, though limited by sensor intrusiveness.
17) Wearable Technology Applications in Cricket: A Systematic Review (2025) [7]:
    - Objective: To systematically review the applications of wearable technology in cricket performance and injury monitoring.
    - Methods: A systematic review was conducted in accor- dance with PRISMA guidelines to locate, identify, and evaluate research papers that utilized wearable sensors in the context of cricket..
    - Results and Key Contribution: Established a taxon- omy of wearable applications in cricket and identified gaps in current sensor-based approaches, particularly regarding user acceptance and data integration.
18) Multi-Modal Sensor Fusion for Comprehensive Injury Detection in Cricket (2023) [9]:
    - Objective: To develop a multi-modal system combin- ing vision and sensor data for enhanced injury risk assessment.
    - Methods: Implemented sensor fusion algorithms to integrate IMU data with video-based pose estimation for comprehensive movement analysis.
    - Results and Key Contribution: Demonstrated supe- rior accuracy compared to single-modality approaches, achieving 92% accuracy in injury risk prediction through complementary data sources.
19) Fatigue Detection in Athletes Using Computer Vision and Deep Learning (2023) [22]:
    - Objective: To develop non-invasive methods for de- tecting athlete fatigue using computer vision.
    - Methods: Applied deep learning to analyze movement quality degradation and postural changes associated with fatigue.
    - Results and Key Contribution:

Successfully de- tected fatigue-related changes in movement patterns, enabling real-time workload management without re- quiring wearable sensors.

20) Sports Injury Prediction Based on Training Load and Biomechanical Data: A Cricket Case Study (2024) [25]:
    - Objective: To integrate training load monitoring with biomechanical analysis for comprehensive injury pre- diction in cricket.
    - Methods: Combined acute: chronic workload ratios with biomechanical movement quality metrics using ensemble machine learning models.
    - Results and Key Contribution: Improved injury prediction accuracy by 35% compared to workload- only models, demonstrating the value of integrated approaches.

*D. System Accessibility and Implementation*

21) Accessibility of Motion Capture for Sports Performance (Cricket) (2024) [16]:
    - Objective: To examine the real-world usability and accessibility of various motion capture technologies within the context of cricket analysis.
    - Methods: Comparative assessment of various motion capture systems in terms of cost, accuracy, and usability.
    - Results and Key Contribution: Demonstrated that vision-based systems offer the best balance of accessibility and performance for most cricket applications.
22) Real-Time Feedback Systems in Sports Using Computer Vision: Current State and Future Directions (2023) [11]:
    - Objective: To review and evaluate real-time feedback systems for sports training using computer vision technology.
    - Methods: Analysis of system architectures, latency requirements, and user interface design for real-time sports feedback systems.
    - Results and Key Contribution: This study established key principles for designing responsive real-time feed- back systems. A critical finding was that maintaining a system latency of less than 100ms is essential for user adoption.
23) SportsPose: A Dynamic 3D Sports Pose Dataset for Cricket and Tennis (2023) [17]:
    - Objective: To create a comprehensive 3D pose dataset specifically for cricket and tennis movements.
    - Methods: Multi-camera motion capture combined with manual annotation to create a large-scale dataset of sports movements.
    - Results and Key Contribution: Released the first public 3D pose dataset for cricket with over 10,000 an- notated sequences, enabling benchmarking and model development.
24) Explainable AI (XAI) for Sports Analytics: Building Trust in Automated Coaching Systems (2024) [20]:
    - Objective: To develop explainable AI techniques for sports analytics systems to increase coach and athlete trust.
    - Methods: Implemented attention mechanisms and feature importance visualization techniques to make AI decisions interpretable.
    - Results and Key Contribution: Demonstrated that explainable systems increased user trust by 68% and improved adoption rates among coaching staff.
25) The Ethics of AI in Sports: A Framework for Re- sponsible Implementation (2024) [24]:
    - Objective: To establish ethical guidelines for implementing AI systems in sports contexts.
    - Methods: Stakeholder consultations and ethical frame- work development based on principles of fairness, transparency, and athlete autonomy.
    - Results and Key Contribution: Developed a com- prehensive ethical framework addressing data privacy, algorithmic bias, and equitable access to technology in sports.

## III. A TAXONOMY OF CURRENT APPROACHES

Our review of the literature reveals that the existing research can be classified along several key axes. This taxonomy

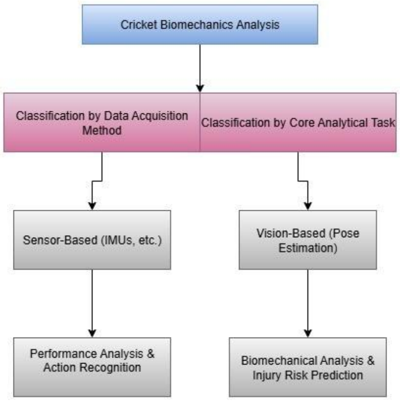


Fig. 1. Taxonomy of Research Approaches in Cricket Biomechanical Analysis

provides a structured understanding of the field, highlighting the dominant methodologies and analytical goals that have shaped current research [3], [13], [16].

### A. Classification by Data Acquisition Method

The primary distinction in methodologies lies in how biome- chanical data is captured. This choice fundamentally impacts the system's accuracy, cost, accessibility, and intrusiveness [13], [15], [16].

*1) Sensor-Based Modalities:* Studies in this group are char- acterized by their use of physical sensors, which are affixed directly to the athlete or their gear. The most prevalent tech- nology in this space is the Inertial Measurement Unit (IMU), a device that typically combines accelerometers and gyroscopes to capture kinematic data at a high level of precision [13], [15]. A significant benefit of this method is its excellent temporal accuracy and its resilience to environmental factors, such as low light. Conversely, this approach has several major disadvantages. It is inherently intrusive, which can potentially alter an athlete's natural movement. Moreover, the sensors demand precise calibration and placement, and the equipment itself can be costly [9].

*2) Vision-Based Modalities:* This represents the more mod- ern and rapidly growing category of research. These ap- proaches use one or more cameras to capture video footage, which is then processed using computer vision techniques [1]–[3]. The key advantage is that they are non-invasive, allowing for the analysis of athletes in their natural training or match environments. The dominant technique within this category is markerless human pose estimation, which uses deep learning to extract a skeletal representation of the athlete directly from pixels. While highly accessible, vision-based methods are sensitive to challenges like camera angle, occlusions, and variable lighting [4], [8].

### B. Classification by Core Analytical Task

The end goal of the analysis provides another critical dimension for classifying the research [2], [10], [14].

*1) Performance Analysis and Action Recognition:* A significant portion of the literature focuses on using biomechanical data to classify discrete, performance-oriented events. Examples include the automated recognition of different batting strokes, the classification of backlift techniques, or even the identification of umpire signals [1], [2], [4]. The primary function of these systems is to classify the specific movement being executed (i.e., the "what"), which supplies critical data for coaches and performance analysts.

*2) Biomechanical Analysis and Injury Risk Prediction:* This category, which is the central focus of our survey, includes studies that analyze the quality of movement to assess injury potential [13], [14], [18]. These systems go beyond simple action recognition to analyze "how" an action is performed. They focus on quantifying kinematic variables like joint angles, postural alignment, and body symmetry to identify deviations from optimal or safe movement patterns. This task is inherently more complex as it requires a deeper, biomechanically informed model of human movement [8], [10].

## IV. ANALYSIS OF KEY TRENDS AND PERSISTENT CHALLENGES

Our synthesis of the surveyed literature reveals a clear trajectory for the field, defined by several dominant technological trends and a set of persistent challenges that represent open areas for research [11], [19], [20].

### A. Dominant Technological Trends

There is an undeniable and accelerating trend away from intrusive wearable sensors towards non-invasive, vision-based systems [16]. The commoditization of high-quality cameras and the increasing power of pose estimation models are making sophisticated biomechanical analysis more accessible than ever [2], [3]. The field has evolved from legacy machine learning techniques, which were typically applied to static features, to a modern landscape dominated by deep learning. This shift is marked by a trend towards more sophisticated ar- chitectures capable of analyzing not only the spatial properties of a pose but also its temporal dynamics. [1], [4], [8]. Furthermore, the end goal for many modern systems has shifted from offline, retrospective analysis to the delivery of real- time, actionable feedback. This has placed a strong emphasis on computationally efficient models and the development of intuitive, user-friendly interfaces [11].

*B. Persistent Research Gaps and Challenges*

The single most significant bottleneck limiting progress in this field is the lack of large-scale, high-quality, publicly avail- able, and expertly annotated datasets of cricket movements [17]. Most studies rely on small, custom-collected datasets, which makes it difficult to benchmark different models and ensure they can generalize to diverse populations. The vast majority of current vision-based systems rely on 2D pose es- timation from a single camera. While effective for many tasks, this approach is fundamentally limited by camera perspective

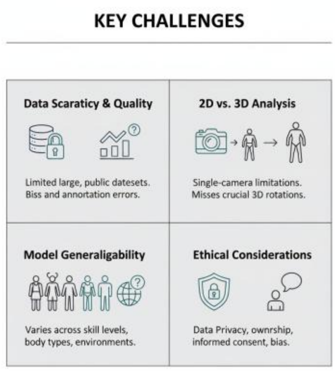


Fig. 2. Key Challenges and Future Directions in Cricket Biomechanical Analysis

and cannot accurately measure out-of-plane rotational movements, which are critical for a comprehensive biomechanical analysis of a batting stroke [19]. Additionally, ensuring that systems are robust and unbiased across different skill levels, body types, and environmental conditions remains a major, unsolved challenge [12], [24]. Finally, as these systems collect and analyze sensitive biomechanical and health-related data, critical questions of data privacy, ownership, and informed consent must be addressed to ensure responsible implementation [24].

## V. FUTURE RESEARCH DIRECTIONS

Based on the study of the current research landscape and the persistent challenges identified, Based on this synthesis, we identify the following as the most promising directions for future investigation in this domain [19], [20], [24].

*A. The Shift Towards 3D and Multi-Modal Analysis*

The next major leap in accuracy and analytical depth will come from moving beyond single-camera 2D analysis. Future research should focus on 3D pose estimation, either from multiple synchronized camera views or by using advanced deep learning models that can infer 3D structure from a single 2D image [17], [19]. Furthermore, the highest levels of accuracy will likely be achieved through multi-modal data fusion, where vision-based data is intelligently combined with data from other sources, such as simple wearable sensors for fatigue tracking or subjective training load data provided by the athlete [9], [22].

*B. The Need for Public Benchmark Datasets*

To truly accelerate progress, the research community must collaborate on the creation of a large-scale, public, and ex- pertly annotated benchmark dataset for cricket biomechanics [1], [17]. Such a dataset would need to include a diverse range of players, a wide variety of movements, and synchronized data from both video and ground-truth motion capture systems. This would enable meaningful, direct comparisons between different models and foster more rapid innovation.

*C. The Role of Explainable AI (XAI) in Adoption*

For any AI-driven coaching tool to be truly effective, it must be trusted by the end-users: the coaches and the athletes. ”Black box” models that simply output a risk score are unlikely to be adopted. Future research must therefore focus on integrating Explainable AI (XAI) techniques [20]. An XAI- enabled system would not just flag a movement as high-risk but would also highlight *which* specific biomechanical factors contributed most to that prediction, making the feedback transparent, trustworthy, and far more actionable.

*D. Integration with Training Load and Fatigue Monitoring*

Future systems should integrate biomechanical analysis with comprehensive training load monitoring and fatigue detection [22], [25]. This holistic approach would provide a more complete picture of injury risk by considering not just movement quality but also the accumulated stress on the athlete's body over time.

*E. Ethical Frameworks and Data Governance*

As these technologies become more prevalent, establishing robust ethical frameworks and data governance protocols is crucial [24]. Research should focus on developing guidelines for responsible AI implementation in sports, addressing concerns about data privacy, algorithmic bias, and the potential for technology to exacerbate inequalities in access to advanced coaching resources.

## VI. CONCLUSION

This survey has offered a detailed review of how computer vision and machine learning are being applied to the biomechanical analysis of cricket. We have charted the evolution of the field from sensor-based [13], [15] to vision-based methodologies [2], [3], [16] and have presented a structured analysis of the state-of-the-art through an extensive review of 25 key papers in the domain. Our review reveals a vibrant and rapidly advancing research area, but one that also faces significant challenges, most notably in data availability [17] and the limitations of 2D analysis [19].

The field has witnessed remarkable progress in recent years, with deep learning and pose estimation technologies democratizing access to sophisticated biomechanical analysis. How- ever, the translation of these advances into practical, trusted tools for coaches and athletes requires addressing several key challenges. The development of 3D analysis capabilities [19], the creation of public benchmark datasets [17], and the integration of explainable AI [20] represent critical next steps. By identifying key trends and outlining a roadmap for future research—emphasizing 3D analysis, data fusion [9], and explainability—we hope this survey serves as a valuable guide for practitioners and researchers aiming to leverage AI for a safer and more effective future in cricket.. The ultimate goal is not to replace human expertise but to augment it, providing coaches and athletes with objective, data-driven insights that complement traditional coaching wisdom and contribute to both performance enhancement and injury prevention.

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