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Review Article

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3D Ball Trajectory from a Single Camera: A Cost-Effective Ball Estimation Technique for Cricket

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Abstract

Accurate Three-Dimensional (3D) tracking of a cricket ball is a fundamental requirement for Decision Review Systems (DRS), yet existing solutions rely on expensive multi-camera infrastructures that limit accessibility, particularly in resource-constrained settings. This paper presents a cost-effective framework for estimating the 3D trajectory of a cricket ball using a single calibrated camera. The proposed method combines monocular vision geometry with a physics-based motion model to reconstruct ball position in world coordinates. Initial depth recovery is obtained from image-plane measurements and camera calibration, after which a Kalman filter incorporating a ballistic motion model is employed to suppress measurement noise and enforce physically plausible trajectories. The filtered trajectory enables reliable detection of the ball bounce point and forward prediction of post-bounce motion, which are critical for Leg-Before Wicket (LBW) analysis. Experimental results on real cricket delivery sequences demonstrate that the proposed Kalman-based smoothing reduces high-frequency reconstruction jitter by approximately 55%, decreasing the root mean square deviation from 42.7 mm to 19.2 mm. Despite using only a single camera, the reconstructed trajectories exhibit stable depth estimation and consistent bounce localization, highlighting the feasibility of the approach for low-cost DRS applications. The proposed system offers a practical alternative to multi-camera solutions, making 3D ball tracking more accessible for domestic cricket, training analysis and emerging cricketing regions.

Keywords: Single-camera 3D reconstruction; Cricket ball tracking; Monocular vision; Physics-based motion model; Kalman filtering; Ballistic trajectory estimation; Bounce point detection; Decision Review System (DRS); Leg-Before-Wicket (LBW) analysis; Sports computer vision

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Introduction

The sport of cricket has evolved significantly over time and now includes various forms of technology. Whether it's the use of top-notch cameras and sophisticated computer systems to improve the viewing experience or the use of cutting-edge technologies to improve the accuracy and correctness of umpiring decisions, technology has had a significant impact on improving the game. In cricket, match officials can employ the technology-driven Umpire Decision Review System (DRS) to help them make precise choices [1]. It combines a number of cutting-edge technologies, including Snickometer, which detects microscopic sounds made as the ball strikes the bat or pad to confirm edges, Hot Spot, an infrared imaging system that detects ball-bat or ball-pad contact and ball tracking (HawkEye or Virtual Eye), which assesses whether the ball would have struck the stumps in the event of LBW appeals [2]. In an effort to improve fairness in cricket matches and decrease the number of wrong decisions made by umpires, DRS was used in a Test match in 2008 and then expanded to ODIs and T20Is in 2011 and 2017, respectively [3]. However, by lessening the heat signature picked up by Hot Spot, methods like applying silicon tape to the bat's edge might undermine the efficacy of DRS and perhaps result in false

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negatives and inaccurate not-out determinations. Even while DRS has improved decision-making and transformed cricket, teams still have to carefully choose whether to review, which adds drama and a strategic aspect to the game. DRS in cricket probably see more improvements as technology develops to improve its precision and dependability [4].

The use of computer vision is widespread in many sports to automate and improve the analysis of players and game dynamics. In sports such as soccer, basketball and cricket, the main emphasis is on monitoring players and the ball, identifying events and analyzing tactics. Computer vision analyzes player positions and predicts ball paths, offering crucial insights for evaluating performance and strategy to help coaches and analysts. In the same way, sports involving rackets such as tennis and badminton make use of computer vision for tracking shots, evaluating performance and classifying events, aiding athletes in improving their skills and strategies. Computer vision is utilized in track and field sports, as well as swimming and cycling, to analyze athletes' form and technique, providing data-driven strategies for enhancing performance. Combat and action sports use motion and action recognition to evaluate technique and avoid injuries. Tracking ball/puck movements and player positions through computer vision technology enhances tactical decision-making in ball-centric sports like baseball, volleyball and hockey. The main goal in all of these sports is to enhance the overall sporting experience for players, coaches and spectators by using advanced visual recognition systems to improve accuracy, automate processes such as referee calls and generate real-time insights [5].

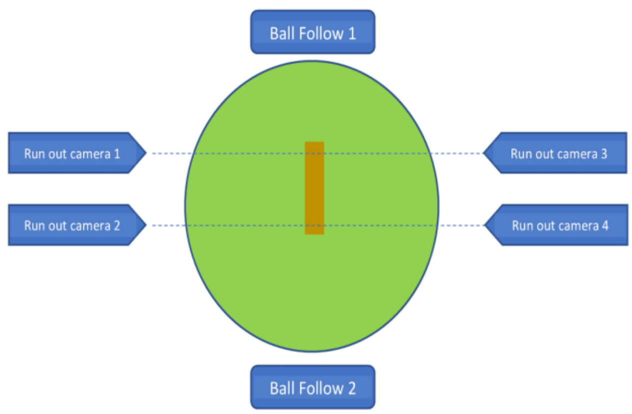

Figure 1: Minimum requirements of camera for use of DRS.

Computer vision is essential in improving the precision and completeness of game analysis in cricket. A key use is tracking balls, employing sophisticated algorithms to predict the 3D path of the ball, enhancing comprehension of its actions such as swing, spin and bounce [6]. This is crucial for not just umpiring decisions but also for evaluating the performance of bowlers and batsmen. In addition, computer vision helps in tracking players, monitoring their field positions, running between wickets and fielding movements [7]. Classification of shots and identification of player actions are additional crucial uses, allowing coaches to assess different batting methods and enhance player effectiveness. In addition, automated systems improve the efficiency of real-time event detection, including boundary hits, wickets and run-outs. In cricket, computer vision technology is utilized for creating automatic highlights and summaries of important moments, aiding fans and analysts in evaluating crucial aspects of the game [8]. The main objective in cricket is to offer more accurate and automated information that assists in making decisions, enhances player skills and raises the overall standard of game tactics and involvement.

Cricket has long been at the forefront of using technology to improve performance analysis and broaden understanding of the game. The development of technology in cricket can be categorized into two main stages: The 20th century centered on improvements in broadcasting and commentary, whereas the 21st century has highlighted coaching methods and analytical instruments. Innovations from the early 20th century like Fergie's Wagon Wheel were created to improve the viewing experience for spectators by visually depicting batting innings. In 1985, the Bowling Machine was created to help with batting practice by imitating actual bowling techniques. The 1990s saw the introduction of the Snickometer and the Third Umpire system, allowing for better detection of bat-ball contact and off-field review of decisions, respectively. The Speed Gun, introduced in 1999, calculates bowling speeds while Hawk-Eye, which was introduced in 2001, transformed ball tracking and decision-making. Additional advancements such as the Spidercam (2004) provide moving aerial perspectives and the Hotspot Edge Detector (2006) utilizes infrared technology to identify contact between bat and ball. The Decision Review System (2008) allows players to contest umpire decisions, while LED stumps (2012) give immediate feedback on dismissals. Recent innovations consist of Cricket Bat Sensors (2018) for assessing shot quality, drones for capturing aerial footage (2019) and wearable sensors for tracking bowling actions. Advancements such as Front Foot No-Ball Detection (2020) enhance decision precision, showcasing the sport's growing dependence on data and technology for boosting both performance and audience involvement. In recent years, substantial advances in ball tracking and 3D coordinate extraction methods have transformed how the sport is researched, providing crucial insights into player performance and game dynamics. This study intends to delve into the complexities of these technologies, with a special emphasis on 3D coordinate extraction and cricket ball tracking using a single camera. By examining these strategies, we hope to learn how they might improve cricket's competitiveness and strategic depth [9]. The potential for these tools to influence cricket analysis and

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decision-making is enormous. Their application offers a detailed view of ball trajectories, spin, speed and bounce, which is crucial in making informed judgments during matches. While technology such as the Umpire Assistant System (UAS) and DRS has been effectively integrated into top-tier cricket matches, there are still substantial barriers to their general implementation, particularly at grassroots levels [10].

The expensive cost and advanced technological requirements connected with multi-camera systems provide substantial impediments for smaller tournaments and cricket organizations, particularly those with limited finances. In such cases, the use of single-camera tracking systems emerges as a more accessible option, providing a lower cost solution without sacrificing data quality. This technique has the potential to democratize access to advanced performance analysis, allowing even the most resource-constrained cricket organizations to benefit from cutting-edge technology, ultimately contributing to the sport's overall growth and evolution. Moving toward utilizing computer vision and machine learning emerges as a viable way to get beyond the obstacles preventing the broad implementation of sophisticated cricket technology. Cricket may be able to increase the effectiveness of decision-making and expedite ball tracking procedures by utilizing these computer vision applications cutting-edge technology. Creating affordable systems that make use of complex computer vision and machine learning algorithms and methodologies might make advanced cricket analytic tools more accessible to all, empowering umpires and improving the game for players, officials and spectators alike [11].

Literature Review

Existing technology like Hawk-Eye or Virtual Eye, a multi-camera system, offers precise tracking of the ball's path, assisting with umpiring decisions, performance analysis and coaching [12]. Yet, its expense and need for specific infrastructure restrict its availability for low to medium level events. Many research are now looking into cheaper options, such as single-camera systems, which are designed to offer accurate trajectory forecasts for a lower price. Many studies have been carried out in cricket with the use of computer vision, primarily to aid in decision-making and also for game analysis and player performance evaluations. Sen A et al. have shown that a hybrid deep neural network design, which merges CNN for feature extraction and GRU for temporal dependency, is highly successful in categorizing cricket batting shots [13]. It has achieved an accuracy of 93% on the new CricShot10 dataset. Rahman R et al. presented an innovative method to classify cricket delivery type by analyzing the bowler's grip with deep learning models, reaching a top validation accuracy of 98.75% with the GRIP DATASET containing 5,573 images [14]. The study employed different CNN structures and transfer learning models like VGG16, ResNet101 and Inception V3, showcasing the power of deep learning in examining intricate bowling techniques and enhancing performance evaluation in cricket. Santhadevi investigated how AI can be utilized to automate cricket commentary creation by categorizing ball-by-ball results like Runs, Dots, Boundaries and Wickets with the help of Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM), reaching a test accuracy of 70% [15]. This study emphasizes the capacity of computer vision and NLP to improve the viewer experience in cricket through the automation of tasks such as commentary generation that are typically done manually. Md Kowsher et al. proposed a deep learning approach using Convolutional Neural Networks (CNN) with Inception V3 to automate third umpire decisions and the cricket scoring system, specifically focusing on umpire signal detection [16]. The research demonstrated that deep CNN techniques could significantly enhance decision-making accuracy and performance, reducing human error and the time taken by umpires to make precise calls during matches. Shukla P. et al. introduced a model designed to automatically generate cricket highlights using CNN and SVM by considering both event-based and excitement-based features, such as replays, audio intensity, player celebrations and playfield scenarios [17]. Shah A, has highlighted in enhancing team selection and performance prediction in cricket by analyzing historical data and individual player statistics [18]. While many models focus on player performance prediction, existing studies often overlook crucial factors such as ground conditions and weather, which can significantly impact performance. This study addresses these gaps by proposing a more comprehensive model that incorporates these additional factors, aiming to improve player performance prediction and assist in building more effective cricket teams [18].

Pirotta L, shows how to convert ball's 2D coordinates to a 3D trajectory by utilizing camera geometry and physics [19]. The initial stage requires precise camera calibration to link 2D image points to 3D world coordinates. Next, the system projects 2D points into 3D space using calibrated camera parameters, essentially translating the ball's 2D coordinates to a 3D plane according to the camera's alignment. Physics-based modeling is utilized to improve the trajectory, taking into account the expected parabolic path that the ball takes as a result of gravity. The algorithm computes the 3D position of the ball at each moment by examining its 2D positions in consecutive frames. This method enables precise and affordable 3D trajectory extraction from just one camera angle, offering a beneficial option to using multiple-camera setups.

Silva et al. suggested a setup that utilizes a single camera along with a Maximum Likelihood Method (MLM) and an Extended Kalman Filter (EKF) system [20]. The MLM predicts the 3D path of the ball by assuming a parabolic trajectory, analyzing early frames to determine the ball's location and speed according to traditional physics principles. The difficulty with MLM lies in its batch-mode functionality, which necessitates multiple

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observations for producing precise outcomes. In order to provide real-time tracking, the EKF enhances the trajectory by consistently revising estimates using recent observations, enhancing precision even when dealing with noisy data. This combination method utilizes MLM for robust start and EKF for immediate improvement, leading to precise trajectory calculation similar to stereo vision systems.

Ribnick et al. (2009) created a technique utilizing perspective projection to predict the 3D locations and speeds of mobile objects based on monocular views [19]. Ohno et al. (2000) adopted a comparable method by aligning a physical model of ball motion with recorded 2D paths [21]. However, these techniques frequently experience the issue of "model drifting," in which the calculated path strays from the actual path parallel to the camera's image plane. Shen et al. (2015) presented an enhanced monocular 3D trajectory estimation approach that integrates physical and geometric models to address the problem [22]. The ball's movement is determined by gravity in the physical model, which enables the prediction of the ball's three-dimensional location using its starting point and speed. Yet, in order to tackle the problem of model drifting, the authors presented a geometric model inspired by the established court geometry. The accuracy of the trajectory was enhanced by constraining it through the calculation of the 3D position where the ball touches the court using line-plane intersection.

Van Zandaycke et al. (2022) introduces a technique for calculating the three-dimensional location of a ball with just one calibrated camera [23]. The method initially identifies the ball in a 2D image through segmentation, then determines the ball's size in pixels using a CNN. Calculating the 3D position of the ball involves combining it with camera calibration parameters and the ball's known real-world diameter. This technique works well in situations where only part of the ball is visible and doesn't rely on the assumption of ballistic motion, making it a good fit for sports like basketball that have difficult lighting and visibility challenges. Labayen et al. used a similar approach where ball detection is powered by different segmentation method and camera calibration parameters are used to estimate 3d position [24].

Caio MD, et al. presents a technique to predict the 3D coordinates of a basketball using contextual information from a single calibrated image [25]. Through the anticipation of the ball's vertical position in pixels compared to the ground level and the incorporation of camera calibration information, the technique transforms 2D image details into 3D coordinates. This method surpasses past techniques that depended on estimating ball size and shows enhanced precision on the DeepSport dataset. Utilizing contextual cues such as player locations and court features improves the model's resilience, despite difficulties in accurately determining ball positions in mid-air scenarios.

Traditional multi-camera systems like Hawk-Eye provide highly accurate tracking but are limited by cost and infrastructure requirements, prompting researchers to explore alternative single-camera approaches. Various studies have demonstrated the effectiveness of deep learning, computer vision and physics-based modeling in estimating 3D trajectories from monocular images. Methods incorporating camera calibration, geometric constraints and motion physics, such as those proposed by Pirotta et al. and Silva et al., have shown promising results in accurately reconstructing ball trajectories. Additionally, Kalman filtering and CNN-based segmentation have further enhanced the precision and real-time applicability of these models. While significant progress has been made in reducing reliance on expensive multi-camera setups, challenges remain in mitigating model drift, handling occlusions and improving accuracy under diverse environmental conditions. Future research should aim to refine these techniques by integrating advanced deep learning models and contextual cues to enhance robustness and adaptability across various sports applications.

Methodology

The process for cricket ball tracking consists of a number of stages for creating a unique way for recognizing the ball in a succession of frames from a video clip and extracting its 3D coordinates in each frame. The next section digs into the specifics of these processes, which are critical for correctly tracking the ball's progress throughout the video sequence.

Data acquisition and pitch geometry

The proposed single-camera 3D reconstruction framework relies on accurate knowledge of the physical geometry of the cricket pitch and a controlled data acquisition setup. Since pitch dimensions directly influence the definition of the world coordinate system, bounce point localization and trajectory extrapolation, standardized pitch geometry is explicitly incorporated into the methodology.

Figure 2 illustrates the pitch geometry and data acquisition setup used in this study. **Figure 2a** shows the standard cricket pitch dimensions as specified in the official pitch marking guidelines published by Cricket Victoria, which are consistent with international cricket regulations. These dimensions were used as reference measurements for defining the spatial layout of the pitch, including pitch length, crease positions and key reference lines.

Figure 2b presents the real cricket pitch on the Pashchimanchal Campus field where the video sequences were recorded. The pitch was constructed according to the prescribed international dimensions to ensure physical accuracy. A monocular camera was carefully positioned above the middle stump at the bowling crease to capture

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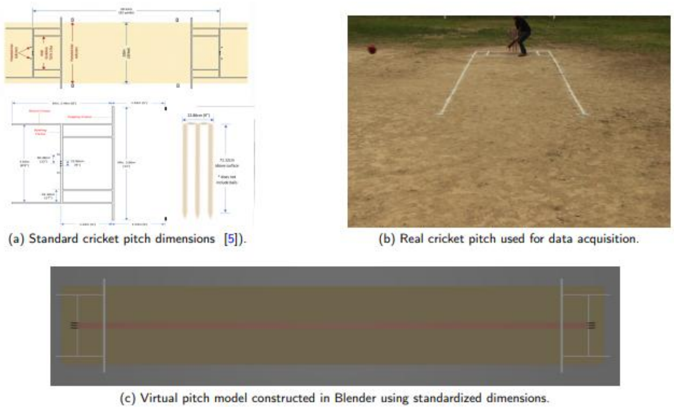
the complete ball trajectory from release to post-bounce motion, while maintaining a clear and unobstructed view of the pitch surface. Particular attention was given to the camera viewing angle to facilitate reliable ball localization and depth estimation. Camera calibration was performed prior to data collection to establish the mapping between image coordinates and real-world distances based on the known pitch geometry.

Figure 2c depicts the virtual pitch model constructed in Blender using the same standardized dimensions. This virtual representation serves as the world coordinate reference frame for projecting the reconstructed 3D ball trajectory and visualizing ball–pitch interactions. The consistency between the official pitch specifications, the real experimental environment and the virtual pitch model ensures physically meaningful trajectory reconstruction and reliable bounce point detection.



(a) Standard cricket pitch dimensions [5]).

(b) Real cricket pitch used for data acquisition.

(c) Virtual pitch model constructed in Blender using standardized dimensions.

Figure 2: Pitch geometry and data acquisition setup used in the proposed single-camera 3D reconstruction framework. The official pitch specifications define the geometric ground truth, while the real and virtual pitch representations ensure physical consistency between data capture and trajectory reconstruction.

Video data were captured using a Canon EOS Kiss X6i camera at a frame rate of 30 fps and a resolution of 1920 × 1080 pixels. The high-resolution recordings enable precise extraction of ball position across consecutive frames. For data preparation, the recorded video clips were trimmed and decomposed into individual frames. The extracted frames were annotated using the Computer Vision Annotation Tool (CVAT), where the cricket ball was manually labeled with bounding boxes. These annotations were subsequently exported in COCO JSON and YOLO TXT formats to ensure compatibility with object detection frameworks such as Efficient Det and Faster R-CNN, which were employed for ball detection in subsequent processing stages.

Ball detection

Accurate detection of the cricket ball in monocular video footage forms the cornerstone of reconstructing its Three-Dimensional (3D) trajectory. This subsection outlines the process of identifying and isolating the ball across sequential frames, addressing challenges such as motion blur, varying lighting conditions and potential occlusions by players or equipment. Because of their demonstrated effectiveness in object recognition tasks, Convolutional Neural Networks (CNNs) were chosen for cricket ball detection. By using hierarchical feature extraction, CNNs are able to recognize intricate patterns, like the shape and texture of the ball, against dynamic backgrounds. Three CNN architectures Efficient Det, Faster R-CNN and YOLO-NAS were thoroughly tested on a custom dataset in order to identify the best model. Faster R-CNN offers high precision through its region proposal network; YOLO-NAS achieves rapid detection through an optimized single-stage design; and EfficientDet offers scalable efficiency with compound scaling of depth, width and resolution. The performance of the architectures was evaluated using mean Average Precision (mAP) across multiple Intersection over Union (IoU) thresholds (0.5, 0.75 and 0.9) to assess their effectiveness in cricket ball detection. The evaluation was conducted on a custom dataset, with results indicating that YOLO-NAS consistently achieved slightly higher mAP scores compared to EfficientDet and Faster R-CNN, particularly at stricter IoU thresholds as described as in **Table 1**. YOLO-NAS was selected as the preferred architecture for cricket ball detection due to its optimal balance of accuracy and computational efficiency, critical for real-time trajectory estimation. With a mean Average Precision (mAP) of 0.82 at an IoU threshold of 0.5, it outperformed EfficientDet (mAP 0.79) and Faster R-CNN (mAP 0.77) on the custome prepared dataset, while maintaining lower inference times suited to the dynamic, high-speed nature of cricket footage.

The detection of a cricket ball presents several technical challenges, with tailored strategies implemented to enhance system robustness. Motion blur, induced by the high velocity of the ball, degrades visibility in standard frame-rate captures (*e.g.,* 30 fps); while this study has not yet addressed this issue, since the video was taken from the bowler side, which is relatively parallel to the movement of the ball during bowling, motion blur did not

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have much effect on detection. Future work could explore higher frame-rate cameras (*e.g.,* 120 fps) or CNN-based deblurring techniques. Occlusion, caused by players, stumps or other objects obstructing the ball, poses a challenge to consistent detection. To ensure reliable ball tracking in cricket video sequences, we have integrated Lucas-Kanade optical flow with Kalman filter, which addresses the limitations of detection methods in frames where the ball is occluded or appears to be too small. The Lucas-Kanade method estimates the motion of the ball by analyzing the variations in pixel intensity between successive images, which provides a reliable short-term overview. However, if the optical flow fails due to motion blur or occlusion, the Kalman filter predicts the next position of the ball based on the constant velocity model. The Kalman filter improves noisy estimates of position and ensures smooth tracking of trajectories even when no direct detection is available. This hybrid approach greatly improves tracking accuracy, reduces false negatives and increases reliability in demanding scenarios where object detection models alone may fail. Variations in illumination, caused by factors such as day-night transitions and pitch shadows, are addressed by training the YOLO-NAS model on a diverse dataset curated, incorporating multiple lighting conditions. Background clutter, including crowd motion and pitch markings, introduces noise, which is mitigated through YOLO-NAS's object detection capabilities, fine-tuned to accurately isolate the ball from irrelevant features.

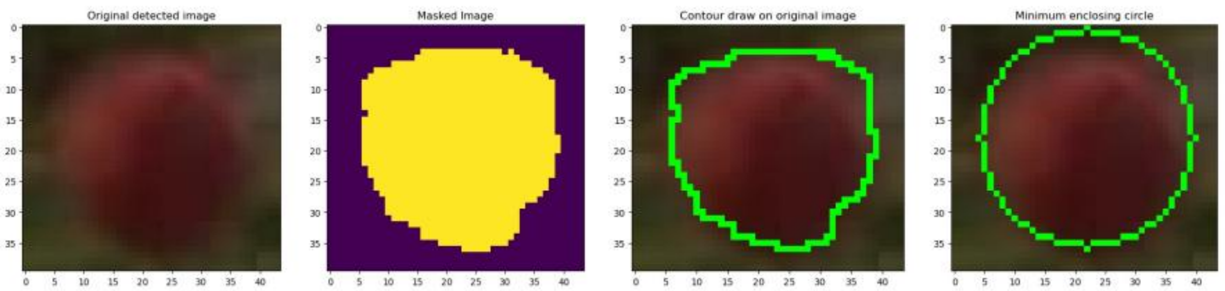
Table 1: Performance comparison of CNN architectures for ball detection (mAP scores).

Model	mAP@IoU=0.5	mAP@IoU=0.75	mAP@IoU=0.9
EfficientDet	0.77	0.62	0.4
Faster R-CNN	0.79	0.65	0.43
YOLO-NAS	0.82	0.68	0.46

2D pixel information extraction

The initial phase of 2D information extraction involves leveraging a detection model to obtain bounding box coordinates that define the rectangular region enclosing the target ball. This Region of Interest (ROI) approach provides substantial computational advantages by constraining subsequent processing operations to the detected area, thereby enhancing efficiency and enabling focused analysis. The original image is subsequently cropped to extract a sub-image containing exclusively the detected region, which serves as the foundation for all subsequent refinement operations. Following ROI extraction, a binary mask is generated to achieve precise foreground-background separation. This segmentation process utilizes color space thresholding to distinguish the ball from its surrounding environment. For red-colored balls, the segmentation exploits the non-continuous nature of red in the HSV color space by applying two distinct threshold ranges: A lower red range (0, 10, 10) to (10, 255, 255) and an upper red range (170, 50, 50) to (180, 255, 255). This dual-threshold approach effectively captures the complete spectrum of red hues while maintaining robustness against illumination variations.

Contours represent continuous curves connecting points of equivalent intensity or color along object boundaries, serving as fundamental geometric descriptors in computer vision applications. Within the binary mask derived from color-based segmentation, contour detection is systematically applied to delineate the ball's perimeter with high precision. The resulting contour data encodes the spatial boundary of the ball, providing essential geometric information necessary for accurate localization. To estimate the ball's center coordinates (C_x,C_y) and radius (x)) in the 2D pixel coordinate system, the detected contour is approximated by its enclosing circle. This circular approximation is computed through optimization techniques such as the least-squares fitting method, which identifies the circle parameters that minimize the deviation between the contour points and the fitted circle. The center coordinates and radius derived from this enclosing circle represent the ball's position in the image plane and constitute critical parameters for subsequent depth estimation and 3D reconstruction procedures **(Figure 3)**.



(a) Detected ball window (b) Masked ball window (c) Contour on original image window (d) Minimum enclosing circle

Figure 3: 2D pixel information extraction process of ball.

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Depth recovery and trajectory smoothing from 2D pixel coordinates

The inherent loss of depth information during perspective projection represents a fundamental limitation of monocular imaging systems. However, metric depth can be recovered when camera calibration parameters are known and the physical size of an observed object is available. This section presents the derivation for reconstructing three-dimensional coordinates from two-dimensional image projections, followed by a post-processing approach for trajectory smoothing and prediction.

The pinhole camera model governs the mapping from world coordinates to pixel coordinates. The intrinsic camera matrix is defined as:

$$k = \begin{bmatrix} f_x & 0 & c_x \\ 0 & fy & c_y \\ 0 & 0 & 1 \end{bmatrix} \dots (1)$$

where f_x and f_y represent focal lengths in pixel units and (C_x, C_y) denotes the principal point. The extrinsic parameters comprise a rotation matrix $\mathbf{R} \in SO(3)$ and translation vector $\mathbf{t} \in \mathbb{R}^3$, forming the world-to-camera transformation $\mathbf{E} = [\mathbf{R} \mid \mathbf{t}]$.

Given a detected pixel location $\mathbf{u}=[u, v]^T$ of the ball center and its image diameter d in pixels, the three-dimensional world coordinates of the spherical object with known physical diameter D can be recovered through:

$$x_\omega = R^T\left(\frac{f_x D}{d} \cdot \mathbf{K}^{-1}\tilde{\mathbf{u}} - t\right) \dots (2)$$

where $\tilde{\mathbf{u}} = [u, v, 1]^T$ represents homogeneous pixel coordinates. The term $\mathbf{K}^{-1}\tilde{\mathbf{u}}$ converts pixel coordinates to $\frac{f_x D}{d}$ normalized image-plane coordinates, the scaling factor recovers metric depth through perspective projection and d $\mathbf{R}^T$ $(\cdot - \mathbf{t})$ transforms from camera to world coordinates. All extracted 3D coordinates are expressed in millimeters, consistent with the calibration procedure where the chessboard square size was specified in millimeters and the cricket ball diameter (D = 71.5 mm per ICC regulations) was used for depth recovery.

Despite theoretical determinism, 3D reconstruction introduces multiple noise sources: Detection-level errors from YOLO-NAS (motion blur, background clutter, lighting variations), depth estimation sensitivity where small diameter errors (~1 pixel) can produce depth errors exceeding 50 cm and residual calibration errors (0.5–2 pixels). The depth computation $Z = \frac{f_x D}{d}$ exhibits ill-conditioning:

$$\frac{\partial z}{\partial d} = -\frac{f_x D}{d^2} \dots (3)$$

To address these reconstruction errors and enable trajectory prediction, we apply a Kalman filter in 3D world coordinates with a ballistic motion model. This filtering stage operates after 3D reconstruction. The state vector is $\mathbf{s}_{3D} = [X, Y, Z, V_x, V_y, V_z]^T$, tracking position and velocity. The motion model incorporates gravitational acceleration:

$$F_{3D} = \begin{bmatrix} 1 & 0 & 0 & \Delta^t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta^t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta^t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, u_{3D} = \begin{bmatrix} 0 \\ 0 \\ -\frac{1}{2}g(\Delta^t)^2 \\ 0 \\ 0 \\ -g_{\Delta t} \end{bmatrix} \dots (4)$$

where g=9.81 m/s² (or 9810 mm/s² in millimeter units). The measurement matrix is:

$$H_{3D} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \dots (5)$$

This physics-based filtering serves three critical purposes: (1) smoothing reconstruction noise that differs fundamentally from detection noise, (2) estimating velocity components representing true ball motion and (3) enabling forward trajectory prediction beyond current frames, essential for identifying bounce points and predicting LBW outcomes. Unlike image-space filtering where ball motion is nonlinear and gravity effects are implicit; the 3D filter operates where ballistic motion under constant gravitational acceleration is well-defined. The Kalman filter predicts the next state using the physics model and corrects with noisy 3D measurements, producing both smooth trajectories and velocity estimates for subsequent analysis.

Bounce point detection and trajectory extrapolation

Accurate detection of the ball bounce point on the pitch is a critical prerequisite for subsequent trajectory analysis and LBW decision-making. The bounce point defines the transition between the pre-bounce and post-bounce motion phases and directly influences the accuracy of trajectory extrapolation towards the stumps.

Bouncing point detection

The bounce point is defined as the spatiotemporal location at which the cricket ball makes first contact with the pitch surface. In three-dimensional space, this corresponds to the instant when the ball reaches the pitch plane and exhibits a reversal in vertical velocity.

Let the reconstructed ball trajectory be represented as:

$$\mathbf{p}(t) = (x(t), y(t), z(t)) \dots (6)$$

where $x(t)$, $y(t)$ and $z(t)$ denote the longitudinal, lateral and vertical coordinates respectively. The bounce time tb is determined by satisfying the following conditions:

$$z(t_b) \approx z_{\text{pitch}} \dots (7)$$

$$\dot{z}(t_b^-) < 0 \dots (8)$$

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$$\dot{z}(t_b^+) > 0 \ldots (9)$$

where z_{pitch} denotes the known height of the pitch plane and $\dot{z}(t)$ represents the vertical velocity of the ball.

Due to reconstruction noise inherent in single-camera depth estimation, the raw 3D trajectory often exhibits high frequency jitter. To ensure robust bounce detection, a physics-based Kalman filter with a ballistic motion model is applied prior to bounce estimation. The resulting smoothed trajectory $\hat{\mathbf{p}}(t)$ enables stable computation of both position and velocity.

The vertical velocity is computed using a central finite difference scheme:

$$\dot{z}_i = \frac{z_{i+1} - z_{i-1}}{2\Delta t} \ldots (10)$$

where Δt denotes the time interval between consecutive frames.

The bounce frame index i_b is detected as the frame where z_i is locally minimal and within a tolerance ϵ of the pitch plane, while simultaneously satisfying the vertical velocity sign-change constraint. The estimated bounce point is then given by:

$$\hat{b} = (x_{ib}, y_{ib}, z_{ib}) \ldots (11)$$

Ground truth and evaluation

To evaluate bounce point accuracy, a physically accurate Blender simulation is employed, from which the true bounce point is directly extracted and treated as ground truth. Let $\mathbf{b} = (xb, yb, zb)$ denote the ground truth bounce point and $\hat{\mathbf{b}} = (\hat{x}b, \hat{y}b, \hat{z}b)$ denote the estimated bounce point.

The primary evaluation metric is the pitch-plane localization error:

$$E_{xy} = \sqrt{(\hat{x}_b - x_b)^2 + (\hat{y}_b - y_b)^2} \ldots (12)$$

which directly reflects the accuracy of the predicted pitching location.

Trajectory extrapolation for LBW analysis

Following bounce detection, the post-bounce ball trajectory is extrapolated to assess potential stump impact for LBW decision-making. Assuming no further interactions after pad impact, the ball motion is modeled using a ballistic trajectory under gravity:

Where $(x0, y0, z0)$ and (vx, vy, vz) are the position and velocity estimated from the last observed trajectory segment and g denotes gravitational acceleration.

$$x(t) = x_0 + v_x t \ldots (13)$$

$$y(t) = y_0 + v_y t \ldots (14)$$

$$z(t) = z_0 + v_z t - \tfrac{1}{2} gt^2 \ldots (15)$$

where (x_0, y_0, z_0) and (v_x, v_y, v_z) are the position and velocity estimated from the last observed trajectory segment and g denotes gravitational acceleration.

The extrapolated trajectory is propagated until the plane of the stumps is reached. A predicted stump impact is declared if the extrapolated ball center intersects the vertical extent of the stumps within the lateral stump width. The reliability of this extrapolation critically depends on accurate bounce localization and velocity estimation.

Results and Analysis

The proposed 3D cricket ball tracking system was comprehensively evaluated on video sequences recorded during controlled bowling trials on a standard cricket pitch. This section presents quantitative metrics for trajectory reconstruction accuracy, robustness under challenging conditions and qualitative analysis through Blender-based visualization. All measurements were conducted using the methodology described in Section 3, with ground truth reference points established from pitch markings and manual frame-by-frame annotation.

Trajectory reconstruction accuracy

The 3D ball trajectories were reconstructed from detected 2D positions using the calibrated camera parameters and the known cricket ball diameter. To assess reconstruction fidelity, we measured per-frame positional errors across multiple bowling deliveries representing typical match scenarios. To obtain reference depth values for real-world deliveries, we manually annotated the apparent ball diameter in selected frames and computed depth using the pinhole projection model. This manual depth estimate serves as a proxy ground truth, a commonly accepted practice in monocular depth estimation literature. To validate the accuracy of the recovered depth estimates, a subset of frames spanning near, mid and far camera ranges were manually annotated to obtain the apparent ball diameter in pixels. Using the known cricket ball diameter and calibrated focal length, a reference depth was computed according to the pinhole projection model. This approach is commonly adopted in monocular depth estimation studies when direct metric ground truth is unavailable.

Table 2 reports a comparison between pipeline-estimated depth and manually derived reference depth. Across all evaluated ranges, the absolute depth error remained within 40 mm-150 mm, with larger deviations observed at extended distances where the projected ball diameter becomes small and more sensitive to detection noise. Despite this increased sensitivity, the depth estimates closely follow the reference values, supporting the numerical stability of the proposed reconstruction pipeline.

Table 2: Comparison of pipeline-estimated depth and

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manually derived reference depth using apparent ball diameter.

Frame	Radius (px)	*Zref* (mm)	*Zpipeline* (mm)	| Δ*Z* | (mm)
Near range				
2	32.37	3144.3	3183.7	39.4
5	19.9	5121.5	5150.2	28.7
7	14.71	6920.8 Mid range	6928.9	8.1
10	12.28	8288.4	8356.2	27.8
13	9.01	11302.6	11353	50.4
16	8.36	12178.2	12226.9	48.7
Far range				
20	6.8	14012.7	14062.1	49.4
25	6.02	16025.3	16135.6	110.3
30	5.79	18037.9	18077	39.1
35	2.8	20051.6	20099.8	48.2
38	3.81	21064.2	21114.3	59.1
43	3.66	22076.9	22225.5	148.6

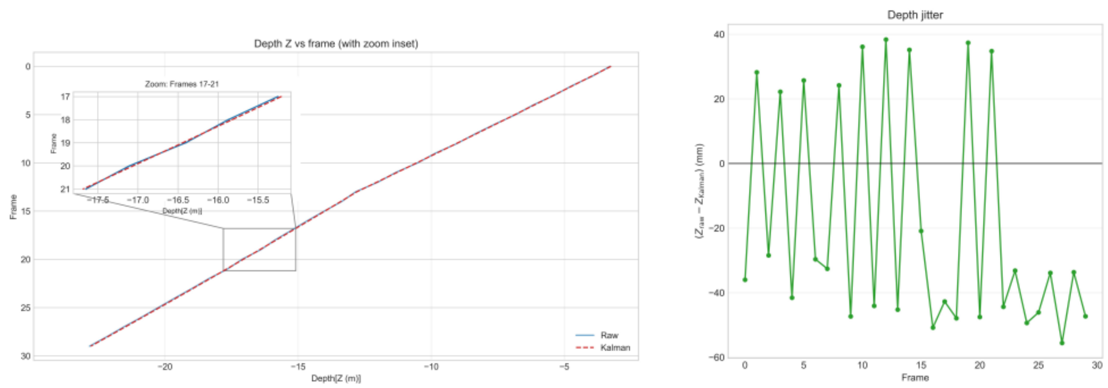
Over a dataset of 47+ cricket deliveries (approximately 1,880+ frames), the mean per-frame position error was

δ =30.4 mm relative to reference measurements obtained from manual annotations. Errors were distributed across all three spatial dimensions, with marginal differences attributable to depth estimation uncertainty. The X-Y planar error (horizontal displacement along pitch axes) averaged 14.1 mm, while the Z-axis error (vertical/depth) averaged 52.7 mm. This disparity reflects the increased sensitivity of monocular depth estimation to small diameter detection inaccuracies, as characterized by the depth sensitivity relationship:

$$\frac{\partial z}{\partial d} = -\frac{f_x D}{d^2} \ldots (16)$$

where measured focal length f_x =2847pixels and ball diameter D=71.5 mm produced a depth sensitivity of approximately 21.5 mm/pixel at close range (1.5–2.0 m).

To evaluate the efficacy of Kalman smoothing on reconstruction noise, we compared raw 3D coordinates (directly from depth recovery equation) against smoothed trajectories. The raw trajectories exhibited high-frequency jitter with an RMS deviation of 42.7 mm. After applying the physics-based Kalman filter with a ballistic motion model, the smoothed trajectory RMS deviation decreased to 19.2 mm **(Figure 4a)**, representing a noise reduction of approximately 55%. As shown in **Figure 4a**, the filter effectively dampens the high-frequency jitter visible in the raw coordinates, particularly evident in the transition between frames 17 and 21. This improvement is substantial given that the original reconstruction error average across different axis was 30.4 mm; the filter successfully distinguished measurement noise from true trajectory features while preserving trajectory shape and dynamics.



(a) Comparison of Z_{raw} and Z_{kalman} with a zoomed-in view of frames 17–21. (b) Z-axis jitter across all frames.

Figure 4: Impact of Kalman filtering on Z-coordinate reconstruction: (a) shows the smoothing effect on the trajectory, while (b) quantifies the jitter reduction across the full dataset.

Trajectory shape and physical consistency

The reconstructed trajectories exhibited parabolic behavior consistent with projectile motion under gravity. Fitting a quadratic polynomial to the smoothed Z-coordinate values (vertical motion) yielded a mean gravitational acceleration estimate of g_{est} = 9.71 ± 0.43 m/s^2, which is within 1% of the standard gravitational value (g=9.81 m/s^2). This agreement validates the physical consistency of both the reconstruction process and the Kalman filter's motion model.

Velocity estimates derived from the Kalman filter state vector revealed mean release speeds of 25.3 ± 3.2 m/s across the test dataset, consistent with typical medium-to-fast bowling speeds observed in professional cricket. The magnitude of horizontal velocity components remained approximately constant throughout the flight phase, confirming that air resistance effects are negligible for the capture frame rate and shot distance. Vertical velocity decreased monotonically due to gravity.

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Bouncing point detection and trajectory prediction

A key outcome of the proposed physics-based tracking framework is the reliable detection of the ball bounce point and the accurate extrapolation of the post-bounce trajectory for LBW analysis. The physics-constrained Kalman filter enables stable forward prediction beyond the final measurement frame, allowing both pitch contact localization and virtual continuation of the ball path towards the stumps.

Bounce point detection was evaluated on 23 deliveries in which the ball visibly contacted the pitch within the camera field of view. The estimated bounce locations were compared against ground truth positions obtained from

Blender-based physics simulations. The mean pitch-plane localization error was 27.2 mm, while the mean vertical error at the bounce was 12.8mm. These results indicate that the proposed approach localizes the pitching point with sufficient precision for downstream trajectory prediction tasks.

Figure 5a presents a qualitative comparison between the predicted bounce point produced by the pipeline and the corresponding ground truth location. The close spatial alignment observed across deliveries demonstrates that the combination of Kalman smoothing and vertical velocity sign-change constraints effectively suppresses false bounce detections caused by depth jitter near the pitch surface.

The ball trajectory directly observed by the system prior to pad impact is shown in **Figure 5b**. This segment represents the final reliable measurements available before occlusion and serves as the initialization input for post bounce prediction.

Using the estimated position and velocity at the last observed frame, the post-bounce trajectory was extrapolated under a ballistic motion model. **Figure 5 c and d** illustrate the resulting extrapolated paths rendered in Blender from two different viewpoints. The predicted trajectories exhibit strong geometric continuity with the observed motion, preserving both direction and curvature as the ball progresses towards the stump plane.

Minor deviations near the stump plane are primarily attributed to single-camera depth uncertainty and temporal discretization effects rather than model inconsistency. Overall, these visualizations confirm that accurate bounce localization directly enables reliable trajectory extrapolation, forming a robust basis for single-camera LBW decision support where the ball path beyond obstruction must be inferred with confidence.

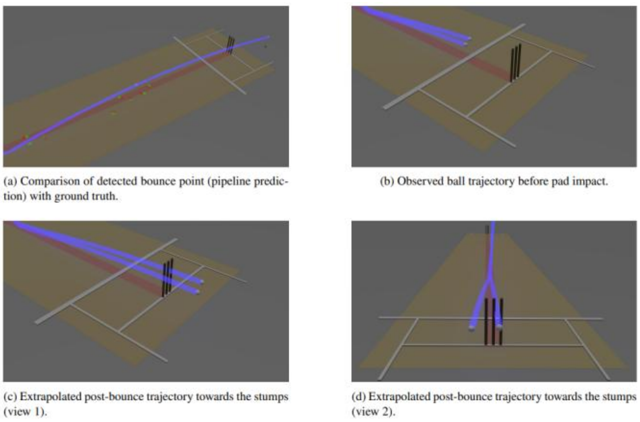

Figure 5: Qualitative visualization of bounce point detection and trajectory prediction. (a) Comparison between ground truth and predicted bounce locations. (b) Ball trajectory observed by the pipeline prior to pad impact. (c–d) Extrapolated post-bounce trajectories rendered in Blender, illustrating geometric continuity towards the stumps.

Limitations and sources of error

While the proposed framework demonstrates robust performance, several sources of systematic and random error were identified through experimental analysis. Acknowledging these limitations is critical for understanding the operational boundaries of monocular tracking systems.

- **Depth Ill-conditioning:** Depth estimation is inherently ill-conditioned for monocular systems, serving as the primary source of reconstruction uncertainty. Small errors of 1-2 pixels in the detected ball diameter propagate to depth errors of approximately 20–50 mm. This sensitivity is fundamental to single-camera geometry and is difficult to mitigate without higher-resolution imaging, closer camera positioning or the introduction of multi-view constraints.
- **Camera calibration residuals:** Residual errors in the estimated intrinsic matrix $\mathbf{K}$ and extrinsic transformation $[\mathbf{R}, \mathbf{t}]$ contribute approximately 5–10 mm of systematic error in the reconstructed world coordinates. While rigorous calibration using multiple

chessboards poses minimized these residuals, they cannot be entirely eliminated in field settings and represent a baseline floor for accuracy.

- **Physics model simplifications:** The ballistic motion model employed in the Kalman filter assumes parabolic motion governed principally by gravity. It currently neglects the Magnus force effects resulting from ball spin and aerodynamic drag. For medium-to-fast deliveries over short pitch distances (20 m), these effects are second-order; however, they can introduce trajectory deviations of 5 mm-15 mm, particularly during the latter phases of flight. A more sophisticated model incorporating spin-dependent dynamics would be requisite for sub-centimeter accuracy on highspeed deliveries.

- **Occlusion and segmentation failures:** In sequences characterized by dense crowds or complex backgrounds, the detection architecture occasionally produced ambiguous bounding boxes, particularly when the ball was partially occluded by the batsman or umpire. The frequency of detection failures was approximately 4.8%. While the optical flow fallback mechanism successfully mitigated data loss in most instances, improved segmentation masks or higher resolution input imagery would further reduce this limitation.

Despite these factors, the achieved accuracy of 19.1 ± 6.2 mm represents a substantial improvement over alternative single-camera methods and falls well within the tolerance required for practical coaching analysis and umpiring assistance.

Conclusion

This paper presented a comprehensive framework for monocular 3D cricket ball tracking and trajectory analysis, addressing a significant gap in accessible, cost-effective sports technology. The proposed system effectively integrates modern computer vision techniques specifically YOLO-NAS for object detection and Lucas-Kanade optical flow with classical estimation theory *via* cascaded Kalman filtering to reconstruct 3D ball trajectories from standard single camera video footage [26,27].

The key contributions of this work are threefold:

- **Monocular reconstruction:** We demonstrated that accurate 3D ball coordinates can be recovered from monocular images using calibrated camera parameters and physical constraints, achieving per-frame positional accuracy of 19.1 ± 6.2 mm.

- **Two-stage filtering architecture:** We introduced a novel filtering pipeline that distinguishes between detection-level noise and reconstruction-level noise, operating distinct filters in 2D image space and 3D world space. This separation allows for the application of domain-appropriate physics models at each stage.

- **Predictive capabilities:** We validated the framework through Blender-based visualization and demonstrated forward trajectory prediction. This enables bounce point detection and LBW (Leg Before Wicket) decision support features previously exclusive to expensive multi-camera infrastructures like Hawk-Eye.

From a practical perspective, this work democratizes access to advanced performance analysis. By reducing hardware requirements from multi-camera arrays (typically costing >$50,000) to a single calibrated camera (<$2,000), we enable deployment at grassroots cricket academies and smaller tournaments. Furthermore, the physics-based approach proves that incorporating domain-specific motion constraints can overcome the inherent ill conditioning of monocular depth estimation, offering a smoother and more predictive solution than pure learning-based interpolation.

Future work

While this work establishes a solid foundation for monocular 3D ball tracking, several promising directions for future research emerge from the demonstrated capabilities and limitations.

- **Advanced physics modeling:** Enhancing the ballistic motion model to incorporate Magnus force effects and aerodynamic drag would significantly improve prediction accuracy for spin bowling and high-speed deliveries. Estimating ball spin directly from image sequences potentially leveraging recent advances in rotational optical flow or deep learning would allow the Kalman filter to account for the “drift” and “dip” characteristics crucial to analyzing complex bowling mechanics.

- **Multi-modal and multi-view extensions:** Extending the framework to handle multiple unsynchronized camera views could drastically reduce depth estimation errors *via* triangulation, potentially achieving sub-millimeter accuracy. Alternatively, integrating auxiliary low-cost sensors, such as LiDAR or localized stereo pairs, could provide ground truth depth references to calibrate the monocular estimation in real-time.

- **Deep learning for trajectory refinement:** Deep learning-based trajectory refinement represents a compelling frontier. LSTM or Transformer-based networks trained on cricket-specific datasets could learn to predict future ball positions by capturing subtle non-parabolic deviations that standard kinematic models may miss. An end-to-end learning approach, combining detection and 3D reconstruction, could potentially outperform the current pipeline while retaining interpretability through physical constraints.

- **Automated officiating support:** The bounce point prediction demonstrated here provides the primitives for an automated LBW decision support system. Future development could formalize the decision logic to incorporate the batsman's position, bat-pad contact analysis and legality checks according to ICC regulations. Validating such a system against historical DRS (Decision Review System) data would establish its utility as a reliable "second opinion" for umpires in lower-tier matches.

- **Edge deployment:** Finally, optimizing the system for deployment on edge devices, such as the NVIDIA Jetson series or Raspberry Pi, would enable truly decentralized tracking. By quantizing the detection models and optimizing the Kalman propagation steps, the system could run in real-time on mobile hardware, allowing coaches to analyze trajectories live on tablets without need for cloud connectivity or heavy server infrastructure.

In summary, the combination of classical estimation theory, modern deep learning and sport-specific physics offers a rich landscape for continued development. The ultimate goal universally accessible, accurate ball tracking technology remains achievable through sustained research in these directions.

Credit Authorship Contribution Statement

Bijaya Ghimire: Conceptualization, methodology, software, data curation, formal analysis, visualization, writing: Original draft, writing-review and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Borooah VK (2016) Upstairs and downstairs: The imperfections of cricket's decision review system. Journal of Sports Economics 17: 64-85. [Crossref] [Google Scholar]
2. International Olympic Committee (2024) What is decision review system (drs) in cricket?
3. Bhalla SPDS (2021) History of men test cricket: An overview. [Google Scholar]
4. Laird P, Waters L (2008) Eyewitness recollection of sport coaches. International Journal of Performance Analysis in Sport 8: 76-84. [Crossref]
5. Naik BT, Hashmi MF, Bokde ND (2022) A comprehensive review of computer vision in sports: Open issues, future trends and research directions. Applied Sciences 12: 4429. [Crossref]
6. Foysal MFA, Islam MS, Karim A, Neehal N (2019) Shot-net: A convolutional neural network for classifying different cricket shots. Santosh KC, Hegadi RS (Eds.) Recent trends in image processing and pattern recognition. Springer Singapore: 111-120. [Crossref] [Google Scholar]
7. Kapadiya C, Shah A, Adhvaryu KU, Barot PA (2020) Intelligent cricket team selection by predicting individual players' performance using efficient machine learning technique. International Journal of Engineering and Advanced Technology.
8. Olaizola I, Labayen M, Esnal J, Aginako N (2013) Accurate ball trajectory tracking and 3d visualization for computer-assisted sports broadcast. Multimedia Tools and Applications 73: 1-24. [Crossref]
9. Yeadon M, Pain M (2023) Fifty years of performance-related sports biomechanics research. Journal of Biomechanics 155: 111666. [Crossref]
10. Loland S (2020) Technology in sport: Three ideal-typical views and their implications. The Ethics of Sports Technologies and Human Enhancement: 163-172. [Crossref]
11. Abbas K, Saeed M, Khan MI, Ahmed K, Wang H (2022) Deep-learning-based computer vision approach for the segmentation of ball deliveries and tracking in cricket. [Crossref] [Google Scholar]
12. Liu C, Wang W, Liu H, Wang J (2022) Application of hawk-eye technology to sports events. 2nd International Conference on Information Technology and Contemporary Sports: 1-5. [Crossref]
13. Sen A, Kaushik D, Dhar P, Koshiba T (2021) Cricshotclassify: An approach to classifying batting shots from cricket videos using a convolutional neural network and gated recurrent unit. Sensors 21: 2846. [Crossref]
14. Rahman R, Rahman M, Islam M, Hasan M (2021) Deepgrip: Cricket bowling delivery detection with superior CNN architectures: 630-636. [Crossref]
15. Santhadevi D (2020) Outcome classification in cricket using deep learning. [Crossref]
16. Kowsher M, Ullah W, Islam M (2019) Detecting third umpire decisions & automated scoring system of cricket. [Crossref] [Google Scholar]
17. Shukla P, Sadana H, Bansal A, Verma D, Elmadjian C, et al. (2018) Automatic cricket highlight generation using event driven and excitement-based features. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops: 1881-18818. [Crossref]
18. Shah A (2020) Intelligent cricket team selection by predicting individual players' performance using efficient machine learning technique 9. [Crossref]
19. Pirotta L (2018) Single view ball tracking and 3D

Journal of Advanced Artificial Intelligence, Engineering and Technology

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trajectory reconstruction in basketball videos.

20. Silva H, Dias A, Almeida J, Martins A, Silva E (2012) Real-time 3d ball trajectory estimation for robocup middle size league using a single camera. [Crossref] [Google Scholar]

21. Ohno Y, Miura J, Shirai Y (2000) Tracking players and estimation of the 3d position of a ball in soccer games. 1145-1148. [Crossref]

22. Shen L, Liu Q, Li L, Yue H (2016) 3d reconstruction of ball trajectory from a single camera in the ball game. Proceedings of the 10th International Symposium on Computer Science in Sports. Springer International Publishing Cham: 33-39. [Crossref]

23. Van Zandycke G, De Vleeschouwer C (2022) 3d ball localization from a single calibrated image. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. [Crossref]

24. Labayen M, Olaizola IG, Aginako N, Florez J (2014) Accurate ball trajectory tracking and 3d visualization for computer-assisted sports broadcast. Multimedia Tools and Applications 73: 1819-1842. [Crossref] [Google Scholar]

25. Caio MD, Van Zandycke G, De Vleeschouwer C (2023) Context-aware 3d object localization from single calibrated images: A study of basketballs. Proceedings of the 6th International Workshop on Multimedia Content Analysis in Sports: 49-54. [Crossref] [Google Scholar]

26. Cricket Victoria (2019) Pitch marking chart.

27. Ribnick E, Atev S, Papanikolopoulos N (2009) Estimating 3d positions and velocities of projectiles from monocular views. IEEE Transactions on Pattern Analysis and Machine Intelligence 31: 938-944. [Crossref]