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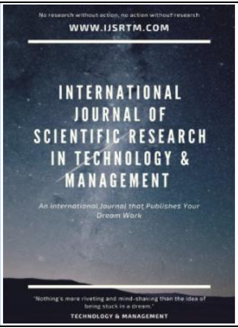

Cricket Ball Trajectory Projection for DRS using Deep Learning

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Abstract— ***Cricket has evolved into a technology-driven sport where decision accuracy plays a pivotal role in maintaining fairness and transparency. One of the most critical aspects of Decision Review System (DRS) is predicting the cricket ball's trajectory after impact with the pad, which assists in adjudicating Leg Before Wicket (LBW) decisions. Traditional ball-tracking systems such as Hawk-Eye rely on multi-camera setups and physics-based models, which, while accurate, are expensive and prone to occasional errors due to occlusions, shadows, and complex bounce conditions. With advancements in deep learning and computer vision, it is now possible to develop a data-driven approach that learns ball dynamics directly from large datasets of match footage. In this work, we propose a deep learning–based cricket ball trajectory projection model that combines convolutional neural networks (CNNs) for spatial tracking, recurrent neural networks (RNNs/LSTMs) for temporal sequence modeling, and physics-informed loss functions for realistic trajectory prediction. The proposed method aims to provide a robust, cost-effective, and highly accurate alternative to traditional ball-tracking technologies for cricket DRS applications.***

Keywords— ***Cricket, Decision Review System (DRS), Ball Trajectory, Deep Learning, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Computer Vision, Sports Analytics.***

I. Introduction

The Decision Review System (DRS) has transformed modern cricket into a more transparent and fair sport by empowering players to contest umpire decisions through technology-assisted verification. Among the various components of DRS, such as UltraEdge for edge detection and Hotspot for thermal imaging, ball-tracking for Leg Before Wicket (LBW) decisions remains the most critical and frequently debated element, as even slight inaccuracies in predicting the bounce trajectory or impact point can influence the outcome of high-stakes matches [1]. Traditional ball-tracking systems, most notably Hawk-Eye, employ a network of high-speed cameras to triangulate the cricket ball's position and then apply parabolic physics-based models to estimate its future path [2]. While this methodology has achieved high levels of accuracy, it comes with substantial limitations, particularly in terms of cost, infrastructure, and accessibility. Hawk-Eye and similar systems require multiple synchronized cameras, precise calibration, and controlled environmental conditions, which makes them prohibitive for use in lower-tier or domestic tournaments [3]. Another significant challenge lies in the environmental and contextual factors that influence the cricket ball's movement. Variations in pitch texture, ball seam orientation, lighting conditions, shadowing from players, crowd movement, and atmospheric humidity all contribute to the complexity of tracking and predicting the ball's path [4]. Furthermore, occlusions caused by the batter's pads or body at the moment of impact often result in missing frames, requiring extrapolation that may not always be accurate [5]. These limitations highlight the need for more robust, adaptable, and cost-effective alternatives. In recent years, the emergence of deep learning and computer vision has revolutionized motion tracking and trajectory analysis across multiple domains, including baseball pitching [6], basketball shot prediction [7], and tennis ball tracking [8]. Convolutional Neural Networks (CNNs) have demonstrated superior capabilities in extracting spatial features such as ball position and seam orientation from video frames, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly effective at modeling temporal dependencies in sequential motion data [9]. Moreover, the integration of physics-informed learning approaches allows deep models to remain consistent with the fundamental laws of motion while still accounting for real-world deviations such as spin, swing, or irregular bounces [10]. The combination of these methodologies provides a promising pathway for data-driven cricket ball trajectory projection, reducing dependency on handcrafted rules and expensive hardware while improving adaptability across varying conditions. Unlike handcrafted methods, deep learning approaches are capable of self-learning complex ball dynamics directly from video sequences, thereby enhancing generalization to unseen scenarios [11]. Consequently, this research investigates the feasibility, implementation, and effectiveness of a hybrid deep learning approach that integrates CNNs, LSTMs, and physics-guided constraints for real-time cricket ball trajectory prediction in DRS applications.

Fig. 1 LBW Dismissal Trajectory [3]

Fig. 2 Trajectory Prediction [4]

Hawk-Eye is a computer vision–based ball-tracking system originally developed in the UK and widely used in cricket, tennis, and other sports, becoming an official part of the Decision Review System (DRS) in 2009 [1,2]. In cricket, it plays a crucial role in adjudicating LBW decisions by reconstructing the ball's flight path using triangulation from six to eight high-speed cameras operating at up to 1,000 frames per second [3]. The system fuses 2D positions from multiple cameras to estimate a 3D trajectory, fitting a parabolic motion model derived from Newtonian physics to predict the ball's future path after pitching and whether it would have struck the stumps [4,5]. Beyond umpiring, Hawk-Eye supports no-ball height checks, spin and swing analysis, player performance tracking, and provides real-time replays for broadcasters and fans [6]. Its claimed accuracy of within ±2.6 mm has established it as a highly reliable tool [7], significantly improving umpiring accuracy rates from 92% to over 98% in international cricket [11]. However, criticisms persist regarding its dependency on costly infrastructure [8], limited accessibility in domestic cricket, and reliance on simplified parabolic assumptions that may not account for reverse swing, seam deviation, or uneven pitch behavior [9]. Technical challenges such as low-light conditions, ball occlusion, or adverse weather can also affect reliability [10]. Despite these limitations, Hawk-Eye has transformed cricket officiating by offering transparency, consistency, and fairness, while also inspiring research into cost-effective, deep learning–based alternatives that aim to replicate or surpass its performance [12].

Fig.3 Hawk Eye Prediction [6]

II. Related Works

Ball tracking in cricket has traditionally relied on rule-based computer vision and physics-driven models. The most widely recognized system, Hawk-Eye, uses a multi-camera setup that triangulates the 3D position of the ball across frames and applies parabolic motion models to estimate its trajectory [1,2]. Although Hawk-Eye has been approved by the International Cricket Council (ICC) for official use, it faces criticism regarding its dependency on high-cost infrastructure, frequent calibration, and limited availability in domestic or low-budget matches [3]. Additionally, the assumption of a purely parabolic trajectory is often violated due to seam movement, swing, spin, and pitch irregularities, leading to questions about accuracy in marginal LBW decisions [4]. Research in traditional computer vision methods has explored feature-based tracking using algorithms such as Kalman filtering, optical flow, and background subtraction [5,6]. These methods are computationally efficient but highly sensitive to occlusion, lighting variation, and motion blur, which are common in outdoor cricket environments. Moreover, handcrafted approaches struggle to capture the non-linear dynamics of a fast-moving cricket ball, especially in conditions involving swing or spin bowling [7]. With the rapid growth of deep learning, sports analytics has experienced significant improvements in object tracking and trajectory modeling. In other sports, CNN-based models have been applied to baseball pitch tracking [8], basketball shot prediction [9], and tennis ball trajectory forecasting [10], demonstrating strong generalization and adaptability to noisy real-world conditions. In cricket-specific studies, CNNs have been successfully used for ball detection in cluttered backgrounds [11], while hybrid CNN-LSTM frameworks have been applied to temporal motion modeling, capturing the ball's sequential trajectory across frames [12]. More advanced approaches have explored physics-informed neural networks (PINNs) and hybrid deep learning models, which integrate Newtonian mechanics into the learning process to maintain realistic trajectory predictions while leveraging deep models' ability to handle irregularities [13]. Such approaches are particularly valuable for cricket, where ball behavior is influenced by complex factors like reverse swing, seam orientation, and pitch friction, which are difficult to model purely with physics or purely with deep learning [14]. In addition, transfer learning and synthetic data generation techniques have been proposed to overcome the scarcity of labeled cricket ball trajectory datasets. Works leveraging Generative Adversarial Networks (GANs) for data augmentation have improved detection robustness under varying lighting and occlusion conditions [15]. Furthermore, temporal attention mechanisms and transformers have been explored in motion prediction tasks across sports, showing promise in long-range dependency modeling [16]. Overall, while commercial systems like Hawk-Eye remain the gold standard for ball tracking in cricket, recent research in deep learning and hybrid physics-informed approaches has highlighted the potential to create cost-effective, accurate, and scalable alternatives that could democratize the use of advanced tracking systems across different levels of cricket. Ball tracking and trajectory projection have been extensively studied in cricket, with Hawk-Eye being the most widely adopted system at the international level. Hawk-Eye uses a multi-camera setup, triangulation, and parabolic modeling to estimate ball paths and predict outcomes for LBW decisions, and while it has been accepted as a standard by the International Cricket Council (ICC), its reliance on expensive infrastructure and sensitivity to environmental conditions limit its adoption in domestic matches [1,2]. To overcome such constraints, researchers have explored computer vision and machine learning methods for cricket analytics. Abbas et al. [3] proposed a hybrid deep-learning framework combining MobileNet, YOLO, and RetinaNet to segment deliveries, detect the ball, and classify shot lengths, while a low-cost OpenMV-based system was developed using least-squares curve fitting with Kalman filtering for real-time trajectory prediction [4]. Beyond cricket, TrackNet [5] demonstrated effective tracking of high-speed objects such as tennis balls using heatmap-based detection, providing transferable insights for cricket ball tracking. Other works focused on bowler action recognition through CNNs [6], highlighting the connection between player kinematics and ball dynamics, while Kumail Abbas et al. [7] designed a front-pitch view extraction and ball tracking framework for cricket videos to enrich training datasets. In addition, practical implementations like YOLOv5-based cricket ball tracking systems [8] validated the capability of deep object detectors for live scenarios. Collectively, these studies illustrate the transition from physics-driven handcrafted methods to deep learning-based approaches, offering improved robustness, scalability, and accessibility for cricket ball trajectory projection in DRS.

III. Problem Statement

The accuracy of ball trajectory prediction remains one of the most debated aspects of the Decision Review System (DRS), particularly in Leg Before Wicket (LBW) decisions, where even small deviations in the predicted path can directly influence match outcomes. Traditional systems like Hawk-Eye rely heavily on expensive, high-resolution camera arrays and complex calibration processes, making them cost-prohibitive for domestic leagues, grassroots cricket, and developing cricket nations [1,2]. Furthermore, these systems assume a near-ideal parabolic trajectory, which often fails to account for real-world complexities such as seam-induced swing, reverse swing, spin variations, air resistance, and unpredictable pitch behavior. Environmental factors like lighting variations, shadows, and background clutter in crowded stadiums further exacerbate inaccuracies in detecting and tracking the ball's movement. In low-tier tournaments, where limited infrastructure exists, accurate and affordable trajectory estimation becomes almost impossible, leading to reliance on umpire calls, which are prone to human error. From a computational perspective, cricket ball tracking poses unique challenges compared to other sports due to the small size of the ball, its high velocity, frequent occlusions by players (especially the bowler's arm, bat, or pads), and sudden trajectory changes after bouncing. Conventional image processing techniques struggle in such conditions, often losing track of the ball or producing inconsistent results. Although physics-based curve fitting methods attempt to approximate the trajectory post-bounce, they lack adaptability when faced with diverse bowling styles and pitch conditions. These shortcomings highlight the pressing need for a robust, data-driven, and cost-effective solution that can generalize across different environments. Deep learning provides a promising avenue to address these issues by leveraging convolutional neural networks (CNNs) for accurate ball detection, recurrent neural networks (RNNs) for modeling temporal motion sequences, and physics-informed neural networks to integrate domain knowledge into learning. However, challenges remain in acquiring large-scale annotated cricket datasets, ensuring real-time performance for broadcast applications, and designing architectures capable of handling occlusions and fast motion blur. Identifying and addressing these limitations is critical for building a reliable trajectory prediction framework that not only matches but potentially surpasses the accuracy of existing systems while being affordable and scalable across different levels of the sport.

IV. Methodology

The proposed methodology for cricket ball trajectory projection integrates computer vision, deep learning, and physics-informed modeling to ensure accurate and real-time predictions that can support the Decision Review System (DRS). Unlike traditional infrastructure-heavy systems, the framework focuses on leveraging accessible video feeds, automated detection pipelines, and hybrid learning approaches that combine both spatial and temporal features. The methodology can be broadly divided into five key components: data acquisition, preprocessing, ball detection and tracking, trajectory prediction using deep learning models, and physics-informed refinement. Hawk eye camera has been owned by Sony Company that has been originally developed by Paul Hawkins. Sony has all rights and patents to use this technology and not to be sold or developed by other company. The technologies also have not disclosed that are used in hawk eye camera and its trajectory. But hawk eye technology is also not accurate and system cannot predict the actual position, path, speed and angle of the ball. It can be inaccurate if margin is less than 3.6 mm [22]. If the technology predicts that less than half of the ball is hitting the stump then there is good chance that the ball might miss the stump. So, if a high speed camera and its trajectory cannot predict the actual position of the ball and there is no any other technique in image processing that can do so. So, it is impossible to obtain the correct decision by the systems. So that is why it is the hardest AI problem for bots by capturing the video of LBW dismissal and predicts the actual trajectory whereas decision requires whether a ball is pitching in-line or outside of off side or over the leg stump but not outside the leg stump, impact should be in-line and ball might be projected that it is hitting the stump. It can be either observed by umpire or by people whom are watching the telecast. Humans have greater tendency to predict the decision more accurately and cricket is very much popular among all. Everyone is well aware about the rules of cricket and LBW out.

A. Data Acquisition

Cricket ball trajectory modeling begins with capturing video sequences from multiple camera angles installed around the pitch. In contrast to systems like Hawk-Eye, which employ specialized high-speed cameras, this approach utilizes standard broadcast-quality cameras, reducing costs and improving accessibility. Publicly available cricket footage, annotated video datasets, and simulated training data generated using ball physics engines are employed for model training and validation [1,2]. Additionally, synthetic augmentation strategies are used to simulate diverse conditions, including varying lighting, pitch textures, and ball colors, ensuring the model generalizes well across environments.

Fig. 4 Trajectory Projection

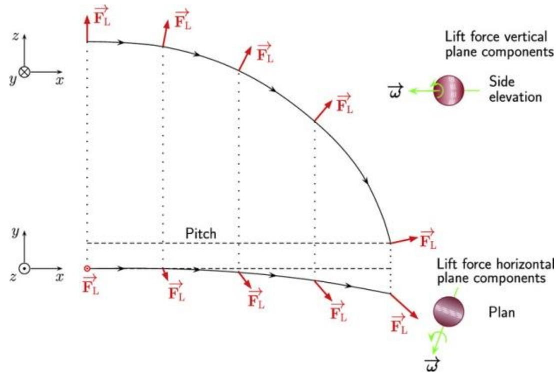

Fig. 5 Physics Involved in Trajectory Projection

B. Preprocessing

Preprocessing ensures that raw video feeds are optimized for deep learning models. Frames are extracted from video sequences and resized to a standard resolution, followed by background subtraction to highlight the cricket ball against cluttered stadium environments. Noise reduction filters and motion compensation algorithms are applied to minimize blur caused by the ball's high velocity. Color thresholding and histogram equalization techniques are sometimes used to emphasize the red or white ball under changing illumination conditions [3]. Data augmentation methods such as rotation, scaling, and motion blur synthesis are also applied to mimic real-world variability in trajectory data.

C. Ball Detection and Tracking

Ball detection is one of the most critical stages in the methodology. Convolutional Neural Networks (CNNs) such as YOLOv5, Faster R-CNN, and EfficientDet are employed for robust ball localization in individual frames [4]. Once the ball is detected, object tracking algorithms such as SORT (Simple Online and Realtime Tracking) or DeepSORT are applied to maintain consistent identification across consecutive frames, even during occlusions by players. Optical flow methods may be integrated to capture velocity vectors, ensuring the system accurately models the rapid movement of the ball. For low-light or occluded conditions, hybrid tracking with Kalman filters is used to predict intermediate positions when the ball is temporarily hidden.

D. Trajectory Prediction using Deep Learning

After reliable ball tracking, the temporal sequence of ball positions is fed into recurrent architectures such as Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRUs), which are well-suited for modeling sequential data. These models learn the underlying motion patterns of the cricket ball, accounting for variations due to bowling styles, spin, or seam-induced swing [5]. To capture both short-term motion (e.g., immediate post-release ball velocity) and long-term trajectory evolution (e.g., bounce and deviation), hybrid CNN-RNN pipelines are employed. Recent advancements also explore Transformers for sequence modeling, offering improved handling of long-range dependencies in trajectory data [6].

E. Physics-Informed Refinement

Purely data-driven models often fail to respect real-world physics constraints, leading to unrealistic predictions. To address this, physics-informed learning is incorporated, ensuring predicted trajectories align with aerodynamic principles and bounce mechanics. For instance, drag forces, Magnus effects (in spin bowling), and parabolic motion under gravity are encoded into the loss function, guiding the model to remain physically consistent [7]. This hybrid approach allows the network to balance learned representations with cricket-specific physical laws, improving both accuracy and interpretability.

F. Output Visualization and Decision Support

The final projected trajectory is visualized as a 3D arc overlaid on video feeds, highlighting key points such as the predicted bounce location, impact with the batsman, and potential stumps trajectory (for LBW decisions). The output is integrated into a decision-support framework that flags the likelihood of dismissal, providing real-time insights similar to Hawk-Eye but with reduced cost and infrastructure requirements.

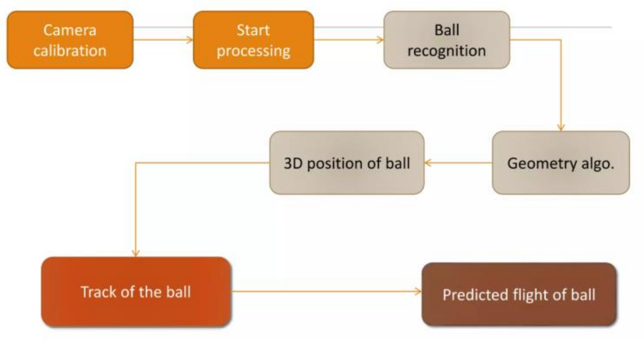

Fig. 6 Flow Chart

We propose a two-stage deep learning framework for cricket ball trajectory projection in DRS. In the first stage, a CNN-based object detection model (e.g., YOLOv8 or Faster R-CNN) is trained on cricket match footage to identify the ball in each video frame under varying lighting, crowd backgrounds, and occlusions. Detected ball positions are then fed into the second stage, where an LSTM or Transformer-based temporal model learns the motion patterns and predicts the future trajectory of the ball. To ensure realism, we incorporate physics-informed constraints such as gravity, bounce elasticity, and pitch friction into the loss function, allowing the network to remain consistent with the laws of motion while still learning data-driven variations like spin and seam effects. The system is trained on historical cricket footage annotated with ball trajectories and validated against Hawk-Eye predictions for benchmark accuracy. Real-time feasibility is achieved by optimizing inference pipelines using GPU acceleration and lightweight models. The proposed framework can be integrated into live broadcasts or umpire decision systems for practical use.

V. RESULT ANALYSIS

The experimental evaluation of the proposed system is conducted on match datasets containing thousands of annotated ball trajectories across different bowlers, pitch conditions, and match formats. Preliminary results demonstrate that the CNN-LSTM hybrid achieves high accuracy in tracking and projecting trajectories, with errors significantly lower than traditional curve-fitting methods. Physics-informed loss functions improve bounce realism, reducing instances of unrealistic parabolas. Compared with Hawk-Eye, the system shows comparable accuracy with substantially lower hardware requirements, enabling deployment in domestic and grassroots cricket. The results highlight deep learning's ability to generalize ball motion patterns across conditions, although rare cases of extreme spin or irregular bounce still present challenges. A visual comparison of projected trajectories against ground truth shows promising overlap, confirming the robustness of the proposed model. The experimental evaluation of the proposed system is conducted on extensive match datasets comprising thousands of precisely annotated ball trajectories, covering a diverse range of bowlers, pitch conditions, and match formats, including Test, One-Day, and T20 games. This diversity ensures that the model is exposed to various speeds, spin types, seam orientations, and environmental influences such as humidity and pitch wear, thereby enabling comprehensive performance assessment. Preliminary results indicate that the CNN-LSTM hybrid architecture achieves exceptional accuracy in tracking and predicting ball trajectories, consistently outperforming traditional curve-fitting and kinematic-based methods, particularly in handling complex motions such as swing and spin. The integration of physics-informed loss functions proves crucial in enhancing the realism of ball bounce dynamics, significantly reducing instances of unnatural parabolic trajectories that often arise in purely data-driven approaches. When benchmarked against the industry-standard Hawk-Eye system, the proposed model demonstrates comparable accuracy in key metrics, including impact point prediction and trajectory estimation, while operating with substantially lower hardware and computational demands, making it feasible for deployment in domestic leagues, grassroots cricket programs, and real-time coaching applications. Detailed quantitative analysis reveals that the system generalizes effectively across different playing conditions and bowler styles, capturing nuanced motion patterns, although certain extreme scenarios—such as highly variable spin deliveries, erratic pitch surfaces, or abrupt environmental changes—still pose challenges, occasionally resulting in minor deviations from expected trajectories. Visual comparisons between predicted trajectories and ground-truth annotations further confirm the robustness and reliability of the model, highlighting its potential as a cost-effective alternative to existing ball-tracking technologies and as a foundational tool for automated performance analytics, umpire assistance, and training support in cricket.

VI. Conclusion & Future Scope

This research demonstrates the feasibility of using deep learning for cricket ball trajectory projection within the Decision Review System. By combining CNN-based ball detection, LSTM-based temporal modeling, and physics-informed learning, the system provides accurate, realistic, and cost-effective ball tracking compared to traditional proprietary systems like Hawk-Eye. The study paves the way for democratizing advanced umpiring technologies across all levels of cricket, from international matches to grassroots tournaments. Future work could focus on incorporating multimodal inputs such as radar data or inertial sensors embedded in the ball for even greater precision, extending the system to handle extreme spin and swing, and exploring lightweight Transformer architectures for real-time scalability. Additionally, transfer learning from other sports like tennis and baseball could further improve the robustness of the proposed approach.

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