Bridging Technology and Probability: A Bayesian Model for Enhanced Cricket Officiating

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Abstract
Integrating technology in sports officiating has led to significant advancements in decision-making accuracy, particularly with the implementation of Hawk-Eye technology in cricket. Hawk-Eye employs a deterministic physics-based model to predict ball trajectories and aid umpires in decisions such as leg before-wicket (LBW) calls**. However, limitations include fixed error margins, reliance on predefined extrapolations, and the absence of real-time probabilistic updates. This paper proposes the incorporation of** Bayesian probability models **into Hawk-Eye's framework to enhance decision-making accuracy. Unlike current deterministic models, Bayesian inference would allow** real-time updates **to decision probabilities based on evolving match conditions. Before each match, sample deliveries are bowled under controlled conditions to collect baseline statistics on ball** bounce, deviation**, and** pace**. These data initialize Bayesian priors tailored to the pitch. During the game, every delivery's actual tracked trajectory (from bowler to batsman) refines the real-time probability estimates. The model continuously adapts to evolving factors such as ball wear, pitch degradation, and atmospheric changes, focusing on** immediate conditions **rather than historical bowler trends. Based on theoretical discussions in the paper, there is an indication that this integrated approach can** increase the accuracy and consistency of **LBW predictions as the system learns and adjusts live. We discuss the implications for umpiring accuracy and technology-assisted decisions and outline future research directions for implementing and validating this Bayesian Hawk-Eye model in live cricket matches.**

Keywords: Cricket, Hawk-Eye, LBW, Bayesian theorem, Monty Hall Paradox, Models, DRS, Umpires

I. Introduction

Cricket has embraced technology to assist umpiring decisions, most notably through the Hawk-Eye system used in the Decision Review System (DRS) since 2009.Hawk-Eye was initially developed for TV broadcast coverage and has since been adopted by numerous sports including tennis, cricket, and snooker [2] .Hawk-Eye is a computer vision and trajectory prediction system that uses multiple high-speed cameras to track the cricket ball's flight and project its path. In LBW decisions, Hawk-Eye helps determine whether a ball that hit the batsman's pad would have gone on to hit the stumps by analyzing:

1. Where the ball pitched
2. The point of impact on the batsman
3. The projected path of the ball past the point of impact

The system displays the statistically most likely path of the ball based on the observed trajectory and is accurate within a few millimeters. This technology has improved the consistency of decisions and is accepted by cricket's governing bodies. However, Hawk-Eye is not infallible, and some doubts remain regarding its accuracy under certain conditions. Its predictions rely on a fixed physics model and may not explicitly adjust for dynamic changes such as weather variations or pitch wear during a match. There have been alternative methods discussed, for example, in [3], an innovative algorithm using stereo vision is discussed which provides automated object tracking in relation to calculated ground plane. Another method is discussed in [6], where seismic method using a 48-channel seismic acquisition system, coupled with basic processing, is used to locate the position at which a cricket ball impacted the pitch with an accuracy of ±10 cm. However, in our proposal we will rely on Hawk-Eye since its most established and widely used in cricket.

Bayesian probability offers a powerful framework for improving predictive accuracy by combining prior knowledge with new evidence. Bayes' Theorem allows us to update the probability of an event as more data becomes available, which is ideal for a sport like cricket, where conditions evolve. In cricket and other sports analytics, Bayesian methods have been used to assess player performance and decisions by updating beliefs with match data [4,5]. In the context of ball tracking, a Bayesian approach can continually refine the estimated trajectory outcomes by learning from each delivery bowled. This means the predictive model can adapt in real-time – for example, if the pitch is observed to produce variable bounce or if the ball starts swinging more as it ages, the model updates its parameters accordingly. By integrating Bayesian updating with Hawk-Eye's real-time tracking, we aim to create a system that maintains high accuracy throughout the match, accounting for the actual playing conditions rather than relying solely on pre-set or historical parameters.

The remainder of this paper is organized as follows: First, we review related work and background on Hawk-Eye technology and Bayesian approaches in sports officiating. Then, we detail our proposed methodology, including pre-match calibration and live Bayesian updating. We present theoretical findings and an illustrative theoretical case study demonstrating the model's effectiveness. This is followed by a discussion on the implications for cricket officiating and how the model addresses current limitations. Finally, we outline future research directions and conclude the paper.

II.HAWK-EYE TECHNOLOGY USED IN CRICKET

In the case of LBW decisions, Hawk -Eye is able toproject the likely path of the ball forward, through the batsman's legs, to see if it would have hit thewicket [1]. Hawk-Eye has definitely revolutionized cricket and it says a lot about its impact based on this stat where of the 1201 on-field umpire decisions challenged in Test matches (2009–2014), 310 (25.81%) were overturned [7].

AlsoAccording to [1] Hawk-Eye is also the most critiqued technology used in cricket, meaning there is scope for improvement. One of the goals of the proposed methodology is also to try to remove some of this criticism. Hawk-Eye operates by tracking the ball using high-speed cameras, capturing multiple frames per second from different angles. By applying triangulation algorithms, the system reconstructs the ball's 3D trajectory. For LBW decisions, the system extrapolates the trajectory post-impact to predict whether the ball would hit the stumps.

However, Hawk-Eye follows a deterministic model, meaning:

- It assumes that the ball will continue moving as per physics.
- It does not dynamically adjust probabilities based on evolving conditions.
- It applies fixed margins of uncertainty (e.g., "Umpire's Call") rather than dynamically quantifying confidence.

These constraints highlight the need for a more adaptive decision-making approach. According to [2] The Hawk-Eye system's accuracy in tracking ball trajectory is beneficial, but its predictive ability needs improvements.

III. BAYESIAN PROBABILITY

Bayesian probability provides a framework for updating decision probabilities as new evidence is gathered. The theorem states:
P(H|E)=P(E|H)·P(H)P(E)P(H|E)=P(E)P(E|H)·P(H)where:

- P(H|E)P(H|E) :
  This is the posterior probability (updated belief about event H given new evidence E).
- P(E|H)P(E|H) :
  This is the likelihood of event happening (probability of observing E if H is true).
- P(H)P(H) :
  This is the prior probability (initial belief about H before evidence E).
- P(E)P(E):
  This is the marginal probability (total probability of observing E).

This framework allows for dynamic updates, which could help Hawk-Eye improve its predictive accuracy by adjusting trajectory predictions based on real-time conditions, such as wind speed, pitch behavior, and bowler-specific tendencies.

IV. ADVANTAGES OF INTEGRATION OF BAYESIAN THEOREM INTO HAWK-EYE TECHNOLOGY

To address the limitations of Hawk-Eye's deterministic model, this paper proposes a Bayesian-enhanced Hawk-Eye framework, incorporating real-time probabilistic updates. The key enhancements include:

1. Bayesian Trajectory Refinement:
   - Current models extrapolate ball trajectory deterministically.
   - A Bayesian approach would adjust the projected path dynamically, incorporating real-time match conditions.

2. Probabilistic Decision Confidence Scores:
   - Instead of binary "Out" or "Not Out" decisions, umpires receive a probability score indicating the likelihood of a correct decision.

3. Adaptive Margins for Umpire's Call:
   - Instead of a fixed threshold (e.g., 50% of the ball hitting the stumps), Bayesian inference could allow for adaptive thresholds based on match-specific uncertainties.

V. METHODOLOGY

Our methodology integrates Bayesian probability updating with Hawk-Eye's real-time ball-tracking data through a structured approach. The idea is not to replace Hawk-Eye but to add to its capabilities and helping in cases where umpire call needs to be used to make decisions. The key steps are as follows:

1. Before the start of each innings (or match), a set of 10 deliveries is bowledunder controlled conditions on the pitch. Different bowlers (representing various styles: fast, swing, spin, etc.) are asked to bowl these deliveries, ensuring a range of speeds and spin variations are represented.

2. All these balls are bowled with no batsman so that the full trajectory (from hand to where it would hit the stumps or pass them) can be observed.

3. We could also make the players from the teams bowl these deliveries giving them incentives for bowling accurately as well as entertaining the crowd while doing it

4. Hawk-Eye cameras track these deliveries to gather baseline statistics, including:
    - Bounce (e.g., how high the ball rises after pitching, given a standard length),
    - Deviation (lateral movement off the pitch, such as spin or seam movement measured in degrees or distance),
    - Pace through the trajectory (speed before and after pitching).
    - These controlled deliveries serve to gauge the pitch conditions – for instance, a dry, cracked pitch might have variable or lower bounce; a green moist pitch might aid lateral seam movement; heavy overcast air might enhance swing on those deliveries. We record the outcome of each ball in terms of whether it would have hit the stumps. This baseline provides an initial dataset characterizing how the ball behaves on that particular pitch and environment.

5. The idea is to construct the initial prior probabilities for the Bayesian model. This includes defining relevant probabilistic parameters for LBW decisions, such as:
    - The prior probability that a ball will hit the stumps (if not struck by the bat) on this pitch, the probability it will miss the stumps. These can be estimated from the 10 sample balls (e.g., if 6 out of 10 would have hit, we start with .6 and .4).
    - Conditional probabilities related to key factors. For example, probability the ball pitches in line with the stumps given it goes on to hit themand probability the ball pitches in line given it would miss the stumps. Similarly, distributions of bounce height or deviation given these events can be derived. If needed, these priors can be multi-dimensional (for instance, a distribution of possible deviation angles). Essentially, the baseline trials inform how likely a ball on this surface is to fulfill the LBW criteria (pitch in line and hit stumps) versus fail (e.g., bounce too high or deviate away). We encode this information according to the system's prior belief. Notably, these priors are pitch-specific and condition-specific – they do not depend on who the bowler is beyond the variety we ensured in the sample. This aligns with our focus on the immediate context rather than any bowler's historical trend.

6. Once the match begins, each actual delivery provides new data. Hawk-Eye continuously tracks every ball from the bowler's hand, through the bounce (if any), to the point of impact (with bat or pad) or passing the stumps. For our purposes, we are interested in deliveries that hit the batsman's pad – potential LBW cases – but the model also learns from all deliveries in general. After each ball, the model updates its probabilities using Bayes' Theorem. For example, consider the probability that a ball will go on to hit the stumps, given it is pitched in line with the stumps. Initially, from calibration, there was an estimate. Now, suppose a particular delivery pitches in line in the match.

We use the observed outcome of that delivery (did it actually go towards the stumps, or did it bounce over/slide down the leg?) as new evidence. The Bayesian update would be:

Pnew(H|in-line)=Pprev(H)·P(in-line|H)P(in-line),Pnew(H|in-line)=P(in-line)Pprev(H)·P(in-line|H),

Where Pprev(H) was the prior probability of hitting stumps before seeing this ball, and P(in-line) is the overall probability of a ball pitching in line (which itself can be updated over time). In practice, we maintain a running probability distribution of relevant variables (e.g., distribution of bounce heights). Each delivery updates these distributions: if a ball bounces higher than expected, the model adjusts the probability curve for a bounce on this pitch slightly. If a spinner's delivery takes more turn than seen in the baseline, the model increases the expected deviation for future balls. The update formula follows the principle "prior belief + new evidence → updated belief", applied iteratively ball by ball.

VI.DISCUSSION

The proposed Bayesian Hawk-Eye model offers several significant implications for cricket officiating and technology-assisted decision-making:

1) Real-Time Accuracy and Consistency:
   A major advantage of our approach is the consistency in accuracy throughout a match. Traditional Hawk-Eye is highly accurate under stable conditions but may not account for gradual changes explicitly. By continuously learning, the Bayesian model maintains accuracy even as conditions evolve. This means fewer surprises or wrong predictions in the later stages of a game. Umpires can trust that the ball-tracking predictions at the end of the day's play are as well-calibrated as they were at the start because the system has self-corrected using the actual match data.

2) Trust and Transparency:
   Introducing probabilistic outputs (like a percentage chance of the ball hitting the stumps) could enhance transparency in the review system. Instead of treating the technology as a black box that gives an answer, officials and even viewers could be informed of the confidence level of a call. This is in line with Hawk-Eye's own notion of a "statistically most likely path.", but our model makes that statistical element explicit. Such transparency can improve the credibility of decisions. For instance, if an umpire's call is retained because the model says "there's a 60% chance it was hitting", it's clearer that it was a marginal situation. Conversely, if overturned, one could point to a 95% probability given by the model. In high-stakes matches, this level of detail can help teams and fans accept decisions more readily, as the process is data-driven and adaptive, not just a fixed rule.

3) Adaptation to Unusual Conditions:
   There have been instances in cricket where conditions were extreme or unexpected (e.g., an underprepared pitch with exaggerated turn and variable bounce). Under those conditions, static prediction models could falter, and even players struggle to adjust. The Bayesian integration shines in such scenarios because it has no fixed expectation – it will simply adjust as quickly as the data comes in. If 10% of balls begin to shoot through at ankle height due to cracks in the pitch, the model will incorporate that frequency into its predictions. This makes the technology resilient and possibly capable of issuing early warnings. For example, if the model detects a drastic shift in behavior (like

sudden excessive deviation), it could alert officials that conditions are changing (which might even be a safety consideration for batters). While Hawk-Eye alone might show each ball's path, it wouldn't "know" that ball was an outlier versus the new normal,whereas the Bayesian model would quantify that shift.

4) No Reliance on Bowler Identity:

By not using historical bowler-specific trends, the model remains fair and unbiased with respect to who is bowling. Every bowler's deliveries are judged against the same yardstick of the pitch conditions. This is important in officiating; the rules should apply equally, whether it's a world-class spinner or a part-timer delivering the ball. Our model avoids any preconceived notions (conscious or not) about a bowler's likelihood to hit the stumps. It only cares about what has been observed. This could eliminate subtle biases – for instance, a fast bowler known for dippers might traditionally get more benefit of the doubt for LBWs; our system would not factor that in, focusing only on actual swing seen that day.

5) Practical Considerations:

Implementing this system would require some adjustments in the cricket protocol. Bowling 10 extra deliveries per bowler (or collectively 10 deliveries by the team's bowlers) before innings might slightly delay the start or require a brief session reserved for calibration. This could be done during warm-ups with the Hawk-Eye system turned on. The benefit is significant calibration data at the cost of a few minutes. Another consideration is computational: updating probabilities ball-by-ball is easily within modern computing capabilities, especially since Hawk-Eye already processes large data in real time. The Bayesian calculations described (essentially a few multiplications and divisions per parameter) are trivial for a computer to handle in milliseconds. We might integrate this into the existing third umpire's toolkit – for example, as soon as a ball is bowled, the system could update and perhaps display a "live probability profile", on the umpire's screen.One potential challenge is noise in data – Hawk-Eye measurements themselves have some errors. A Bayesian model could inadvertently chase that noise (for example, adjusting probabilities based on what might be a tracking error). To mitigate this, the model can be made robust by incorporating the known error margins of Hawk-Eye into the likelihood functions. Essentially, we would not update dramatically on one ball's evidence if it's within the known error range; we'd update more strongly once a consistent trend is seen. This is a common practice in Bayesian filters (like Kalman filters used in tracking), where you weigh new data by its certainty. As a result, our model can balance responsiveness with stability.

6) Comparison to Other Approaches:

An alternative approach to improving ball prediction could be a purely machine-learning model trained on big data of deliveries. That might capture complex interactions but often acts as a black box and might still struggle with novel conditions outside its training data. In contrast, our Bayesian method is model-driven and interpretable – it explicitly uses probabilities and can easily incorporate human-understood parameters like "windy day increases swing likelihood." Moreover, because we use match-specific priors, we essentially let each match train its ownmodel on the fly, which is more effective than applying generic training to a specific situation. This tailored on-site learning is a unique strength of Bayesian updating in this context.

In summary, the integration of Bayesian probability with Hawk-Eye enhances the system's ability to make accurate, fair, and transparent decisions. It acknowledges that cricket is a dynamic sport where conditions change and treats officiating as an evolving inference problem rather than a static call. Our discussion confirms that such a system is conceptually sound and practically feasible, offering a path forward to more reliable decision aids in cricket.

VII. CONCLUSION AND FUTURE WORK

This paper presents an assessment of Hawk-Eye's current deterministic framework and proposes a Bayesian probability integration to enhance decision-making in cricket officiating. While Hawk-Eye does not currently use Bayesian modeling, this research highlights its potential benefits, including improved accuracy, real-time adaptability, and better uncertainty quantification.

If successful and the models are proving to be accurate there is a chance it can save some of the cost associated with expensive infrastructure needed for Hawk-Eye systems by reducing some of the equipment used for tracking. Future research should focus on:

- Developing prototype Bayesian-Hawk-Eye models for testing.
- Conducting experimental trials with historical match data.
- Working and engagingwith local sports governing bodies to explore the feasibility of integrating this proposed methodology in cricket officiating.

By integrating Bayesian probability, cricket can move towards a more robust and transparent officiating system, benefiting both players and officials.

VIII. REFERENCES

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