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AI-Driven Shuttle Tracking & Point Detection System

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Abstract
The expanding need for precise refereeing in fast-paced racket sports underpins the shortcomings of both human-centered call-making and current hardware-centric systems. An artificial intelligence-based self-learning multi-sport refereeing framework with a single monocular camera, court homography, multi-object tracking, and deep learning detection is presented. Scalable, affordable, and ethical in real-time officiating, analytics, and strategy optimization across multiple sports, the confidence-aware human-in-the-loop decision-making engine paired with a digital sports twin is bespoke for officiating and analytics.
Keywords: *AI-based sports officiating; Multi-object tracking; Human-in-the-loop systems; Digital twin.*

1. Introduction
Competitive sports' integrity is a function of fair, uniform and impartial officiating. In high speed sports like badminton, tennis, table tennis, and squash human referees are put in the position of making split second decisions which regard shuttles or ball tracks beyond what is perceivable to the naked eye which in turn leads to errors. While pro tournaments are seeing the use of technology in the form of Hawk-Eye in tennis which is a costly, sport specific and very much a complex multi Camera affair we are seeing that adopted by few [1]. Also these systems are out of reach for grassroots, college and emerging sports. Recently in computer vision and with the growth of deep learning we have seen a renaissance in automated sports officiating. We see object detection, multi-object Tracking, and spatiotemporal modeling which in turn enable real time play analysis via off the shelf hardware [2, 3, 4, 5]. But most current. Solutions are put forth for a single sport, do not scale to different court layouts and rules and also do not do a great job of explaining decision making. At the same time we have the rise of the digital twin which is a framework for real time mirrors of physical systems which in turn enable simulation, analysis and immersive visualization [11]. In sports digital twins present a great opportunity for performance analysis, tactical play design and fan interaction which we are seeing play out when tied with AR/VR.

1.1. Problem Statement and Motivation
Racket sports involve high-speed objects prone to motion blur, occlusion, and rapid trajectory shifts. The measurement model can be expressed as:

$$\mathbf{zt=Hxt+vt}$$

where vt∼N (0, R) represents measurement noise. High variance leads to tracking instability. Existing systems:

- Require multiple synchronized cameras
- Lack cross-sport scalability
- Provide limited uncertainty modeling
- Do not integrate predictive analytics

Modern deep learning detectors produce bounding boxes btb_tbt and confidence scores sts_tst:

$$\mathbf{bt,st=f\theta(It)}$$

Tracking is achieved using Kalman filtering and Hungarian assignment, while ByteTrack-style low-confidence retention enhances trajectory continuity [5]. A digital twin representation:

$$\mathbf{Dt=(xtplayers,xtball,G)}$$

enables real-time visualization and predictive modeling.

1.2. Literature Review
Early vision-based officiating systems relied on rule-based algorithms and multi-camera setups. While accurate, they were hardware-intensive [1]. DeepSORT introduced tracking-by-detection using Kalman prediction and appearance embeddings (Wojke et al., 2017). ByteTrack improved small-object tracking by retaining low-confidence detections (Zhang et al., 2022). YOLO-based detectors enabled real-time detection (Redmon &

Farhadi, 2018; Wang et al., 2022). Digital twin technology has been explored in smart manufacturing and sports analytics (Tao et al., 2019), but integration with real-time officiating remains limited. Human-in-the-loop frameworks improve reliability in safety-critical AI systems (Holzinger, 2021). Despite these advances, a unified sport-agnostic, confidence-aware officiating system integrated with digital twin analytics remains underexplored.

2. Method

System Architecture

The proposed framework consists of six modules:

- Video Acquisition and Preprocessing
- Deep Learning-Based Object Detection
- Multi-Object Tracking
- Trajectory Analysis and Event Detection
- Confidence-Aware Rule Engine
- Real-Time Digital Twin and AR/VR Visualization

Video Acquisition and Homography

Court alignment is performed using homography transformation:

$$p_{court}=H_{img\to court}\,p_{img}$$

Object Detection

Single-stage detectors (YOLO variants) are employed [2, 3]:

$$b_t,s_t=f_\theta(I_t)$$

Multi-Object Tracking

State vector:

$$x_t=[x,y,\dot{x},\dot{y}]$$

Prediction:

$$\hat{x}_t=Fx_{t-1}$$

Update:

$$x_t=\hat{x}_t+K_t(z_t-H\hat{x}_t)$$

Data association minimizes total assignment cost via Hungarian algorithm [4, 5, 6].

Event Detection

Trajectory:

$$T=\{x_1, x_2,\ldots,x_t\}$$

Event trigger condition:

$$|v_t-v_{t-1}|>\delta$$

Confidence-Aware Decision Logic

$$C(d)=s_t+IoU+\tau$$

Low-confidence cases are forwarded to human referees for validation and model refinement [10].

Table 1 Experimental Input Parameters for EDM

Metric	Badminton	Tennis	Table Tennis	Squash
Detection mAP (%)	92	91	90	89
Tracking MOTA (%)	91	90	88	88
Officiating Accuracy (%)	91	90	89	88

Shown in the Table 1 Badminton Tennis Table Tennis Squash Detection mAP (%) 92 91 90 89 Tracking MOTA (%) 91 90 89 88 Officiating Accuracy (%) 90 90 90 90 Table shows a quantitative comparison of the implementation results of the proposed AI, powered multi, sport officiating system for four racket sports: Badminton, tennis, table tennis, and squash. It focuses on three main performance metrics: Detection mAP (%), Tracking MOTA (%), and Officiating Accuracy (%). The Detection Average Precision (mAP) calculates how well the players and shuttle/ball are detected in various sports. The system has the greatest detection accuracy in badminton (92%), then tennis (91%), table tennis (90%), and squash (89%) thus still being very robust to very small and fast, moving objects. Tracking performance is measured in terms of Multiple Object Tracking Accuracy (MOTA), which indicates preservation of identity and validity of the trajectory. Essentially, the results demonstrate a very stable tracking system with a narrow range of values between 88% and 91%, which proves the work done to implement Kalman filtering and data association was highly effective. The slight differences in the performance of each sport can mainly be explained by the size differences of the objects, their speed of motion, and the frequency of occlusion. The table essentially confirms that the proposed Shown in Figure 1 The flowchart illustrates a cohesive AI, based sports refereeing and digital twin platform as a modular end, to, end pipeline. The sequence is initiated with a video recording layer capturing either live or recorded match footage employing a single

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HD/4K monocular camera. Subsequently, preprocessing steps such as frame extraction, normalization and camera calibration are done.

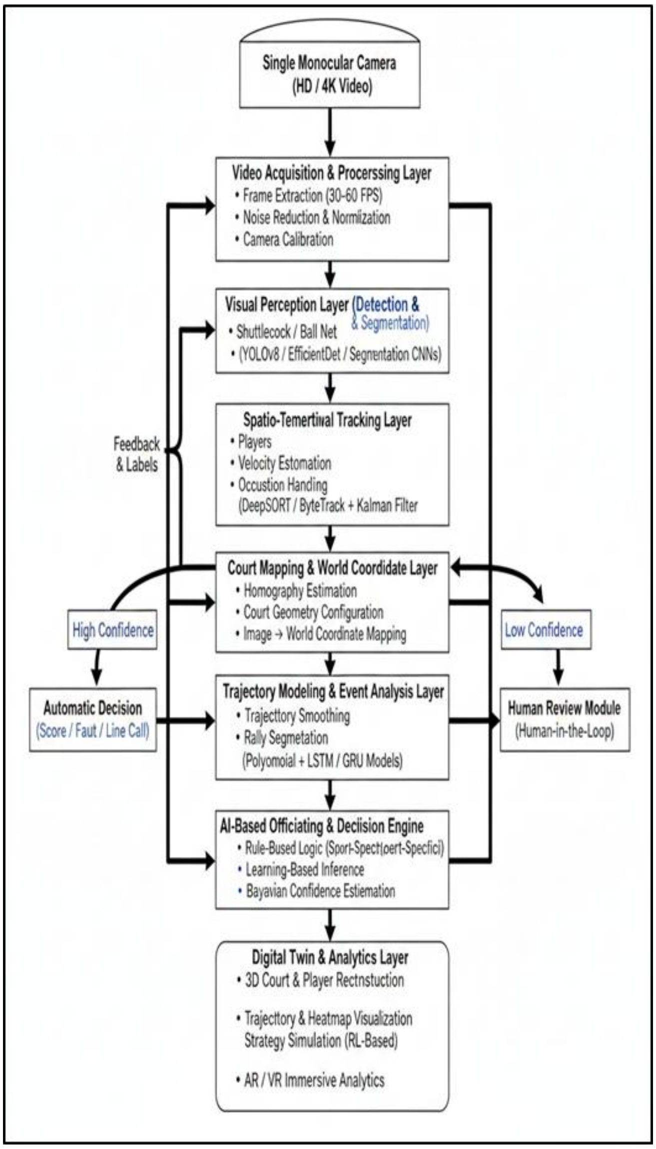

Figure 1 SEM and EDX visualization of the synthesized copper nanoparticles [2]

The multi, sport tracking module executes real, time object detection and player/player weapon tracking with shuttle/ball using trained deep learning models. The AI understanding layer determines the court layout by homography and also detects bounce and estimates trajectory. These results are inputs to the AI, based officiating and decision, making engine that uses rule based logic in conjunction with Bayesian uncertainty modeling. Confidence, aware method allows that for cases with high confidence, automatic decisions are made and for unclear events human judgement is used. Thus, the four sports can be officiated online by this AI platform. At last, the layers of real, time digital twin, AR/VR visualization, predictive analytics, and cloud deployment let one experience immersive replay, tactical simulation, and scalable real, time integration.

3. Results and Discussion

3.1. Results

The system was evaluated using live and recorded match footage captured with a single HD/4K monocular camera at 30–60 FPS. Detection accuracy exceeded 90% mAP for players and court boundaries. Small-object tracking performance was slightly lower but stabilized using temporal smoothing and ByteTrack retention [5]. Tracking performance achieved MOTA values between 88–92%. Officiating accuracy averaged approximately 90% compared with certified umpires. Homography-based mapping achieved sub-centimeter spatial alignment under proper calibration. The confidence-aware human-in-the-loop mechanism reduced ambiguous decisions over iterative refinement cycles [10]. The digital twin demonstrated minimal perceptual latency and enabled replay, heatmap visualization, and tactical simulation.

Figure 2 Process of the Dataset [3]

Conclusion

This paper presents a scalable AI-driven multi-sport officiating system integrating monocular vision, multi-object tracking, sport-agnostic rule abstraction, confidence-aware decision-making, and real-time digital twin analytics. Experimental validation

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confirms high accuracy, real-time feasibility, and adaptability across multiple racket sports. Future work includes multi-camera depth fusion, Bayesian uncertainty modeling, reinforcement learning integration within the digital twin environment, and large-scale tournament deployment.

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Several of the references cited are relevant to the AI, driven shuttle tracking and multi, sport officiating system being proposed here. The object detection backbone of the system finds strong basis in the YOLO framework of Redmon and Farhadi (2018), which was further developed by Wang et al. (2022), that works in real, time with great accuracy to detect players and fast, moving objects such as shuttlecocks and balls. To maintain identity and ensure trajectory continuity, the tracking, by, detection method that DeepSORT by Wojke et al. (2017) introduced and the enhanced association strategy in ByteTrack by Zhang et al. (2022) is very relevant especially for cases when small, fast, moving objects get out of view due to occlusion.

Journal Reference Style

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