

# Umpire AI: An Autonomous Real-Time Basketball Game Analysis and Scoring System Using Deep Learning and Computer Vision

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**Abstract** - Automated sports video analysis plays a crucial role in performance evaluation, tactical assessment, and officiating assistance. Accurate tracking of player movements and object trajectories from broadcast footage enables the computation of speed metrics, interaction dynamics, and structured match statistics. This paper presents a unified deep learning-based framework that integrates YOLO-based object detection, keypoint-based spatial calibration, trajectory interpolation, coordinate transformation, and statistical performance modeling for automated match analysis. The proposed system processes standard video input to detect players and moving objects frame-by-frame, identify event intervals based on trajectory dynamics, estimate real-world speeds, and generate annotated visual outputs along with cumulative statistical summaries. Experimental evaluation demonstrates player detection precision of 93.1% and ball detection precision of 93.3%, with multi-object tracking accuracy of approximately 90%, validating the effectiveness and scalability of the proposed AI-driven sports analytics framework. A web-based deployment interface enables seamless video upload, automated backend processing, and visualization of analytical results.

**Index Terms**—Basketball Analytics, Computer Vision, Deep Learning, YOLO, Multi-Object Tracking, Homography Transformation, Sports Analytics, Event Detection.

## I. INTRODUCTION

Sports video analysis has become increasingly integral to performance evaluation, tactical assessment, and automated officiating due to advancements in computer vision and deep learning technologies [1], [2]. Despite the availability of high-quality broadcast footage, extracting structured performance metrics from raw video remains a complex task. Manual annotation is time-consuming and prone to inconsistency, while professional tracking systems rely on specialized multi-camera installations and dedicated hardware infrastructure, limiting accessibility for research and scalable deployment [3], [4].

Previous research has demonstrated the effectiveness of deep learning approaches, particularly real-time object detection architectures such as YOLO, in identifying and localizing dynamic entities within video streams. However, accurate match analysis requires more than object detection alone. Rapid motion, occlusion, motion blur, and varying camera perspectives introduce significant challenges in maintaining tracking consistency and spatial precision [5], [6]. Furthermore, pixel-based measurements obtained from video frames must be transformed into real-world units to compute meaningful performance metrics.

To address these challenges, the proposed framework integrates object detection, spatial keypoint extraction, trajectory interpolation, coordinate transformation, and statistical computation within a unified processing pipeline. In this work, a hybrid deep learning approach is adopted by combining multiple YOLO variants, multi-object tracking algorithms, and spatial transformation techniques to achieve accurate and scalable basketball game analysis.

## II. RELATED WORK

### A. Object Detection and Multi-Object Tracking in Sports Videos

Early sports video analysis systems relied on traditional computer vision techniques such as background subtraction, optical flow estimation, and handcrafted feature descriptors to detect and track players. Although these approaches demonstrated moderate success under controlled conditions, they were highly sensitive to illumination changes, camera motion, and player occlusion [10]. With the advancement of deep learning, CNN-based object detection frameworks such as Faster R-CNN, SSD, and YOLO significantly improved detection accuracy and real-time processing capability [11], [12].

YOLO-based architectures have gained widespread adoption in sports analytics due to their balance between speed and detection precision. Several studies have applied YOLO variants to detect players and small fast-moving objects such as balls in football, basketball, and tennis matches [13], [14]. Multi-object tracking algorithms such as SORT and DeepSORT have been integrated to maintain temporal consistency of detected entities across frames [15].

### B. Ball Trajectory Modeling and Event Segmentation

Accurate ball trajectory modeling is essential for automated officiating and performance analytics. Traditional approaches employed Kalman filtering and motion vector estimation to smooth object trajectories and predict future positions [16]. Recent research incorporates deep learning-based temporal modeling to improve ball tracking reliability and event detection accuracy [17]. Similar approaches have been applied in basketball to detect passes, shots, and ball possession changes [19]. However, many existing works do not integrate real-world speed computation and cumulative statistical modeling within a unified framework.

### C. Spatial Calibration and Real-World Metric Estimation

Pixel-based measurements extracted from broadcast videos must be transformed into real-world units to compute meaningful performance metrics. Homography-based field mapping techniques have been widely adopted to align image coordinates

with known court or field dimensions [20]. Keypoint detection models further improve spatial calibration by automatically identifying court boundaries and reference landmarks from video frames [21].

#### D. Web-Based Sports Analytics and Automated Deployment

The deployment of AI-driven sports analytics systems has increasingly shifted toward web-based architectures. Lightweight frameworks such as Flask and Django have been used to integrate deep learning inference pipelines with interactive visualization dashboards [23]. Unlike existing approaches that focus on individual components, the proposed system integrates detection, tracking, spatial calibration, and analytics into a unified framework for comprehensive basketball analysis.

### III. PROPOSED ARCHITECTURE

The proposed system presents an intelligent AI-based framework for automated basketball umpiring and game analytics using computer vision and deep learning techniques. The system processes broadcast basketball videos to detect players and ball movements, track game dynamics, and generate real-time analytical insights. The overall methodology is designed as a multi-stage pipeline integrating detection, tracking, spatial transformation, and event analysis modules.

Player detection is performed using a custom-trained YOLOv11 model, which identifies players in each frame and outputs bounding boxes along with confidence scores. The detected players are passed to the ByteTrack algorithm for multi-object tracking, ensuring consistent identity assignment across frames. Ball detection is carried out using a YOLOv516u model specifically trained for small object detection, with the highest-confidence detection retained per frame.

Court structure information is extracted using a YOLOv8x-based pose estimation model trained for 500 epochs to achieve sub-pixel precision, detecting keypoints corresponding to court markings such as sidelines, midcourt line, and free-throw areas. Team classification is achieved using a CLIP-based model that analyzes jersey color and texture.

#### A. Spatial Calibration Using Homography Transformation

Accurate spatial understanding of the basketball court is essential for computing real-world metrics. The proposed system employs a homography transformation technique that maps points from the broadcast camera view to a standardized top-down tactical view. The transformation is computed using keypoints detected on the court to estimate a homography matrix  $H$  that enables perspective correction. Fig. 1 illustrates this process.

$$[x' \ y' \ 1]^T = H [x \ y \ 1]^T$$

where  $(x, y)$  represents the original image coordinates,  $(x', y')$  represents the transformed top-view coordinates, and  $H$  is the homography matrix.

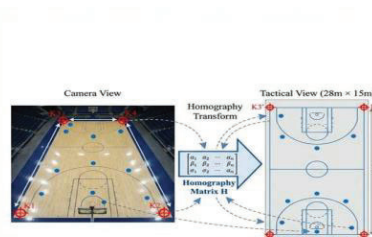


Figure 1: Illustration of Homography Transformation (H) mapping keypoints of the court from a perspective camera view to a rectified top-down tactical view.

Fig. 1. Illustration of Homography Transformation (H) mapping keypoints and player positions from a perspective camera view to a rectified top-down tactical view.

#### B. Court Geometry and Real-World Mapping

To ensure accurate metric computation, the system incorporates a standard basketball court model with predefined dimensions (28m x 15m). Fig. 2 shows the standardized court layout used for spatial calibration. By aligning detected keypoints with this reference model, the system performs scale normalization, perspective correction, and real-world coordinate transformation.

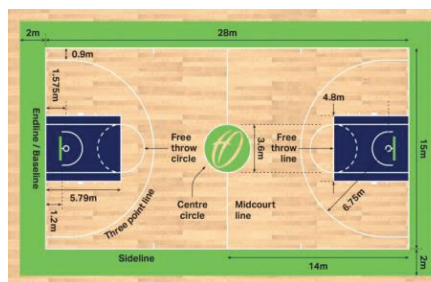


Fig. 2. Standardized basketball court layout (28m x 15m) used for spatial calibration and real-world coordinate mapping.

#### C. Multi-Object Detection and Tracking Framework

The proposed system integrates multiple computer vision modules to detect and track players and the ball simultaneously in real time. Fig. 3 presents the output of the AI-based analysis pipeline, illustrating player tracking, ball detection, court keypoints, and team assignment. The system operates with a batch size of 20 and a confidence threshold of 0.5.

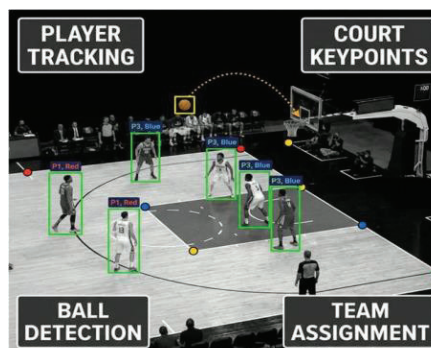


Fig. 3. Example of AI computer vision analysis overlay on a broadcast basketball frame, illustrating multi-object tracking, ball trajectory, and court registration.

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#### D. Ball Track Refinement and Possession Logic

To improve accuracy beyond raw model output, the system implements several algorithmic refinement strategies. The ball tracker includes a `remove_wrong_detections` function that filters physically impossible spikes in ball movement, eliminating false positives caused by large displacements inconsistent with realistic ball physics. An `interpolate_ball_positions` function fills gaps where the ball may be occluded or motion-blurred, ensuring a continuous and smooth trajectory.

Ball possession is determined using a dual-criterion algorithm combining a Containment Ratio measure with a Minimum Distance threshold. Temporal consistency checks are applied across frames to prevent flickering possession labels. Multi-frame averaging further refines keypoint positions, resulting in a more stable homography matrix and improved real-world spatial mapping.

#### IV. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed system was evaluated using basketball match videos under varying conditions including occlusion, fast motion, and multiple player interactions. Performance was assessed using standard detection metrics: Precision, Recall, mAP50, mAP50-95, and F1 score. Validation was conducted over a test set of 5,000 ground truth samples per model.

##### A. Object Detection Performance

Table I summarizes the detection performance of the two core YOLO models. The ball detector (YOLOv5l6u) achieves a precision of 93.3% and recall of 82.8%, with an mAP50-95 of 69.1%. The player detector (YOLOv11) achieves a precision of 93.1%, recall of 86.6%, and an mAP50 of 93.0%, confirming consistent player localization across varied game scenarios.

TABLE I

OBJECT DETECTION METRICS: BALL VS. PLAYER MODELS

Model	Prec.	Recall	mAP50	mAP50-95
YOLOv5l6u (Ball)	93.3%	82.8%	—	69.1%
YOLOv11 (Player)	93.1%	86.6%	93.0%	71.8%

##### B. Statistical Validation: TP / FP / FN Analysis

Table II presents the TP/FP/FN breakdown from validation over 5,000 ground truth samples per model. The ball detector produced 4,140 true positives, 297 false positives, and 860 false negatives, yielding an F1 score of 87.6%. The player detector produced 4,330 true positives, 321 false positives, and 670 false negatives, achieving an F1 score of 89.7%.

TABLE II

STATISTICAL VALIDATION RESULTS (5,000 GROUND TRUTH SAMPLES)

Model	GT	TP	FP	FN	F1
YOLOv5l6u (Ball)	5000	4140	297	860	87.6%
YOLOv11 (Player)	5000	4330	321	670	89.7%

##### C. System-Level Performance Summary

Table III presents a consolidated summary of all system-level performance metrics. Multi-object tracking using ByteTrack maintained a tracking accuracy of approximately 90% with minimal identity switching. Speed estimation error was within  $\pm 1.2$  m/s after homography-based calibration. The court keypoint

model (YOLOv8x-pose) was trained for 500 epochs for sub-pixel precision.

TABLE III

CONSOLIDATED SYSTEM PERFORMANCE METRICS

Component	Metric	Value
Player Detection (YOLOv11)	Precision / Recall	93.1% / 86.6%
Ball Detection (YOLOv5l6u)	Precision / Recall	93.3% / 82.8%
ByteTrack (MOT)	Tracking Accuracy	~90%
Speed Estimation	Mean Abs. Error	$\pm 1.2$ m/s
YOLOv8x-pose (Court)	Training Epochs	500 epochs

##### D. Tracking Reliability and Refinement

To enhance tracking reliability, the system incorporates temporal consistency analysis by examining object motion across consecutive frames. Adaptive confidence thresholding is applied during object detection to handle variations in lighting conditions, motion blur, and scale changes. Moving average filtering is applied to positional data to produce more stable speed and distance measurements.

##### E. Computational Efficiency

The framework enables near real-time processing on GPU-enabled systems. Parallel execution of detection modules and optimized data processing pipelines contribute to improved scalability and faster inference performance, making the system suitable for practical deployment in real-world sports analytics applications.

#### V. CONCLUSION

In this work, a hybrid deep learning framework is proposed that integrates YOLO-based object detection, multi-object tracking, spatial calibration, trajectory modeling, and web-based visualization for automated basketball game analysis. Experimental results demonstrate player detection precision of 93.1% and ball detection precision of 93.3%, with F1 scores of 89.7% and 87.6% respectively. Multi-object tracking accuracy reached approximately 90%, and speed estimation error remains within  $\pm 1.2$  m/s after homography-based calibration.

The integration of ball track refinement, interpolation, and dual-criterion possession logic further improves accuracy beyond raw model output. Future work will focus on extending the system to additional sports, incorporating hoop-zone detection for automated scoring, and developing predictive analytics for enhanced tactical insights.

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