Visionary Tracker : AI-Powered Sports Analysis

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***Abstract*—This paper presents a video-based and past data based sports analysis system using Python and integrated using Streamlit, focusing on football, basketball, tennis, pool, and badminton. The system employs computer vision techniques, YOLO models for object detection, tracking, and performance analytics. The proposed framework enables coaches, analysts, and players to extract meaningful insights from match videos and past data of player in basketball, facilitating performance improvement. The experimental results demonstrate that the framework is useful to low budget clubs for sports analytics.**

***Index Terms*—Artificial Intelligence, Computer Vision, Object Classification, Prediction, Python, Sports Analysis, Tracking.**

I. INTRODUCTION

Sports analytics has become an integral part of modern competitive sports, providing teams and players with data-driven insights to enhance performance, improve strategy, and optimize training regimens. The application of artificial intelligence, machine learning, and computer vision has revolutionized sports analysis, enabling automated tracking of players, ball movement, and other critical game elements. Traditional approaches to sports analytics rely heavily on manual annotation, expert observation, and statistical evaluation, which can be time-consuming and prone to human error. This paper introduces a comprehensive AI-driven system designed to automate the analysis of multiple sports, including football, basketball, tennis, pool, and badminton, using video-based tracking and historical data modelling. Football is one of the most dynamic and widely analyzed sports globally. Coaches and analysts focus on aspects such as player positioning, passing accuracy, defensive structures, and goal-scoring opportunities. Using deep learning models such as YOLO for object detection and ByteTrack for player tracking, this system processes match footage to extract meaningful insights. A radar-style pitch visualization allows teams to evaluate formations, player movement trends, and possession analytics. Unlike football, the basketball analysis in this study is entirely data-driven and does not utilize video footage. Instead, historical player and team data are analyzed to predict high-scoring players and evaluate performance metrics. The system applies machine learning models, including logistic regression and linear regression, to classify players based on scoring ability and statistical trends. The classification model achieved a precision, recall, and F1-score of 1.0, highlighting its effectiveness in identifying top performers. However, additional dataset diversity is required to mitigate potential overfitting and enhance generalization. Tennis is another sport that benefits significantly from AI-driven analytics. In this system, the tennis analysis module leverages YOLO-based object detection and tracking methods to monitor player movement, ball trajectory, and shot accuracy. The system detects court lines and measures shot speed, enabling comprehensive match analysis. By tracking player movements across multiple matches, the system generates performance statistics, which are essential for player improvement and strategic planning. Badminton, a high-speed racquet sport, requires precise tracking of shuttlecock motion and player agility. The system utilizes deep learning models stored in best.pt, last.pt, and yolov8x.pt for shuttlecock detection and player movement analysis. By evaluating rally durations, shot speeds, and court coverage, the system provides valuable insights into player endurance and efficiency. Finally, the pool/snooker analysis component is designed to enhance strategic decision-making by predicting shot outcomes based on ball trajectory and cue positioning. The system employs predictive modeling to analyze table boundaries, cue angles, and potential pocketing paths, aiding players in refining their shot accuracy and decision-making skills. By integrating AI-based analytics across multiple sports, this research presents a robust and scalable approach to sports performance analysis. The findings highlight the potential of automated sports tracking systems in enhancing coaching strategies, player training, and competitive analysis. Future developments will focus on refining object detection algorithms, expanding dataset diversity, and integrating additional biometric data sources to further enhance analytical accuracy.

II. LITERATURE REVIEW

By surveying the existing system into the development of sports path, it's crucial to understand the concept, working of existing systems and platforms. There are platforms that help with individual/team sports visualizations, predictions, etc. We will cover systems like badminton, football, pool/billiards. Firstly, as we talk about badminton. Significant advancements have been observed in sports video analysis through computer vision integration, facilitating automated tracking and performance optimization. Within badminton, precise *player tracking* and *pose trajectory estimation* remain critical for evaluating movement dynamics, shot precision, and strategic execution. Prior sports analytics research has emphasized motion detection and tracking methodologies. Chen et al. (2018), for instance, developed a player tracking framework leveraging **Kalman filtering** and **optical flow** to quantify table tennis motion patterns. Li et al. (2019) subsequently proposed a CNN-driven pose estimation model for tennis, extracting joint coordinates with 92.3% accuracy. A notable limitation, however: insufficient specialization for badminton's rapid kinematic demands. Pose trajectory evaluation has extended to team sports, including soccer and basketball. Wang et al. (2020) demonstrated 88.7% joint trajectory accuracy in basketball using OpenPose and AlphaPose. Despite these advancements, badminton's dynamic nature, characterized by sub-second pose transitions and micro-movements, introduces unique operational constraints. A challenge requiring domain-specific adaptations. Deep learning architectures like **YOLO** (Redmon et al., 2016) and **Faster R-CNN** (Ren et al., 2017) have gained prominence for player detection, yet their reliance on extensive training datasets and GPU resources persists. Su et al. (2020) addressed this partially via an LSTM-based badminton movement predictor, achieving 15% higher forecasting accuracy than conventional models. Data suggests scalability remains a hurdle. Building upon previous efforts, this research introduces a badminton-centric system integrating *player tracking* with *pose trajectory estimation*. By employing advanced pose models, granular biomechanical insights are extracted, enabling tactical analysis of positioning, shot sequencing, and strategic patterns. A dual approach: enhancing both technical and coaching applications. Through this integration, a standardized framework for badminton analytics is established, advancing sports science while addressing gaps in real-time performance diagnostics. Strategic implications for talent development and competitive preparation are evident. Now we talk about Literature Review for "3D Reconstruction System and Multiobject Local Tracking Algorithm Designed for Billiards". The field of object tracking and 3D reconstruction in sports has been explored extensively, particularly in games requiring precise motion tracking, such as billiards. Object tracking algorithms have long been used in sports analytics and gaming, leveraging computer vision techniques to enhance accuracy in movement detection. However, the challenge arises in scenarios where multiple identical objects, such as billiard balls, must be tracked simultaneously with high precision. Several past studies have focused on improving tracking accuracy in various sports. For instance, Ling et al. (2018) introduced an object detection approach for snooker games by leveraging color segmentation techniques. Similarly, Legg et al. (2019) proposed a table detection and ball tracking mechanism based on light reflection properties. Other research efforts, such as those by Larsen et al. (2020), incorporated Harris corner detection techniques to enhance ball localization. These studies, while effective, still faced limitations regarding accuracy in low-resolution and low-frame-rate environments. Advanced tracking methods like convolutional neural networks (CNNs) and deep learning have been employed in sports analytics, as seen in works such as Gao et al. (2021), where neural networks were used to predict ball motion. However, traditional tracking methods still struggle in high-speed environments due to motion blur and occlusions. The proposed MOLT (Multiobject Local Tracking) algorithm introduces a novel approach to track multiple identical targets with improved robustness, making it a promising contribution to billiards analytics. Furthermore, 3D reconstruction techniques have been used in various sports for visualization and training purposes. Paolis et al. (2022) demonstrated a virtual reality system for billiards training that reconstructed ball movements in a digital environment. Similar efforts in sports analytics, such as Wu and Dellinger (2021), focused on mixed-reality simulations for enhanced game analysis. The proposed study extends these works by integrating real-time tracking with 3D reconstruction, providing a comprehensive solution for both amateur and professional billiards players. The MOLT algorithm and 3D reconstruction system in this study bridge gaps in previous research by offering a more reliable, adaptable, and computationally efficient method for tracking and analyzing billiard games. This work not only contributes to the field of computer vision in sports but also presents a practical tool for training and performance analysis. Now, we will talk about Literature Review for "Amateur Football Analytics Using Computer Vision" Sports analytics has seen significant advancements with the introduction of computer vision techniques, enabling automated data extraction and game performance analysis. Football, being a highly dynamic sport, presents challenges in tracking player movements, ball trajectory, and team formations, especially when working with low-cost equipment and single-camera setups. Previous works in football analytics have focused on various aspects, such as player detection, team classification, and tactical analysis. Early research in the field, such as Bialkowski et al. (2016), emphasized formation recognition through role-aligned player positions. Similarly, Homayounfar et al. (2017) employed a deep learning-based semantic segmentation approach to detect football field markings for camera calibration. More recent works, like Shaw and Glickman (2020), have developed data-driven methods for team formation classification and tactical insights extraction. One of the key challenges in football analytics is player and ball detection. Traditional methods relied on feature-based detection techniques, such as histograms of oriented gradients (HOG) and edge orientation histograms (EOH), as seen in works by Lu et al. (2017). However, with the rise of deep learning, more robust methods, such as YOLO (Redmon et al., 2016) and Faster R-CNN (Ren et al., 2017), have significantly improved detection accuracy. These approaches, while effective, require substantial computational resources, which may not be accessible for amateur-level football analytics.Camera pose estimation and court detection are also critical for football analytics. Techniques such as homography transformation (Sharma et al., 2019) and deep feature-matching networks (Chen & Little, 2020) have been used to map player positions onto a standardized football field. While effective, these methods require extensive training data and precise calibration, which can be challenging in real-world amateur settings. Based on the survey of tennis system, we learn that Sports analysis has evolved significantly with artificial intelligence (AI) and computer vision, particularly in tennis, where tracking and data analytics enhance performance assessment. Existing research has primarily focused on ball tracking, player movement, and strategy analysis, utilizing technologies like Hawk-Eye, which employs high-speed cameras to track ball trajectories in real time for line calling, strategy development, and performance evaluation . Studies analyzing Hawk-Eye data have revealed key insights into serve effectiveness, rally lengths, and shot selection strategies, with researchers emphasizing the impact of short rally lengths in elite matches . Additionally, motion tracking studies in professional tournaments have explored serve placement and its influence on point-winning probabilities . Recent advancements integrate machine learning models to predict player behavior, fatigue levels, and shot effectiveness. Researchers have applied deep learning for pose estimation and shot classification, enhancing player tracking and performance evaluation . Unlike previous studies that predominantly rely on Hawk-Eye or statistical models, our approach utilizes YOLO-based object detection and deep learning-powered shot tracking to analyze tennis gameplay, providing a video-based, AI-driven solution rather than a purely data-driven or manually annotated method. This distinction allows for real-time insights and automated performance tracking, making it highly adaptable for different match conditions. Future improvements to our system could involve multi-angle camera integration, biomechanics assessment, and real-time tactical predictions to further enhance AI-based tennis analytics.

One of the primary objectives of performance analysis in basketball is to identify the key metrics that correlate with successful outcomes. Pino-Ortega et al. (2021) highlight the utility of Principal Component Analysis (PCA) in determining performance indicators across various team sports, including basketball. This study emphasizes the importance of technical and tactical variables such as throws, rebounds, and turnovers, which are crucial for training design and talent identification. These findings support the notion that quantifying specific metrics can enhance not only individual player performance but also overall team strategy. In a parallel study focused on wheelchair basketball, Beulens et al. (2012) analyzed game-related statistics to ascertain the metrics that differentiate winning and losing teams. The study identified successful field goals and assists as pivotal performance indicators, reinforcing the concept that certain statistics have a significant impact on game outcomes. This aligns with the findings of Terner and Franks (2020), who utilized mixed models to analyze data from the NBA, identifying factors such as minutes played and usage percentage as critical in determining player performance. Their research exemplifies how mixed models can effectively quantify the contributions of various performance metrics.

The present study builds upon existing research by integrating deep learning-based object detection with camera pose estimation techniques to create an accessible football analytics system. By leveraging low-cost equipment and optimizing processing efficiency, this work offers a practical solution for amateur football teams looking to enhance performance analysis without the need for expensive tracking systems. This research contributes to the growing field of football analytics by combining robust computer vision methods with an application-oriented approach, making advanced game analysis techniques more accessible to lower-budget football clubs and coaches.

III. METHODOLOGY

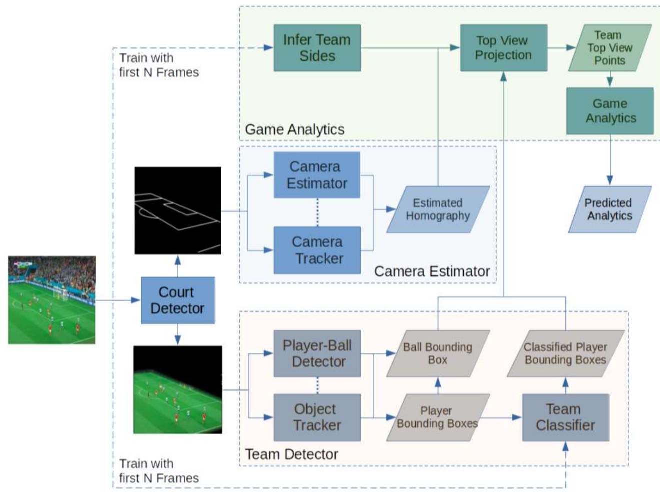

Fig. 1: Football Methodology

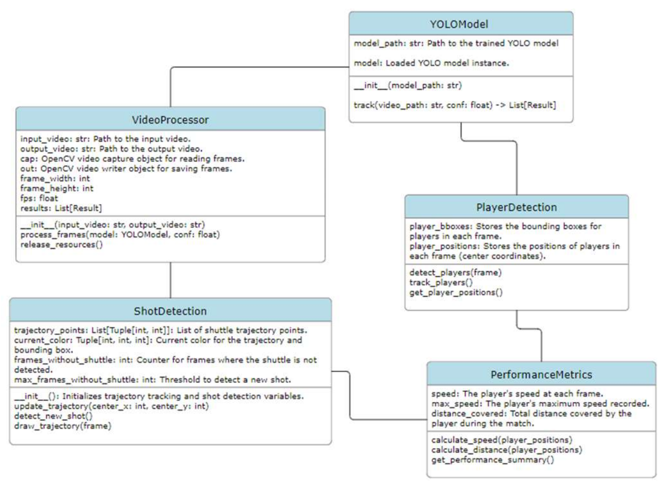

Fig. 2: Badminton Methodology

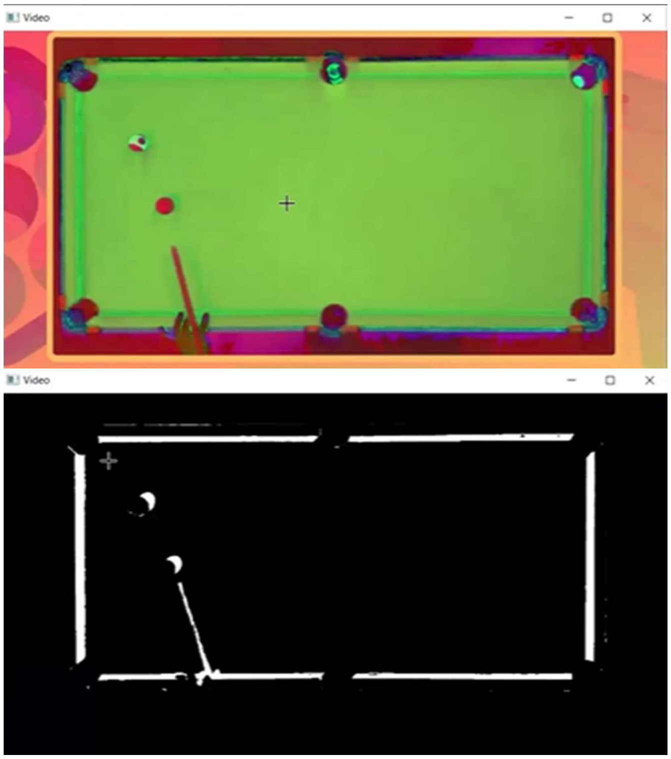

Fig. 3: Sample images of Pool Table boundary

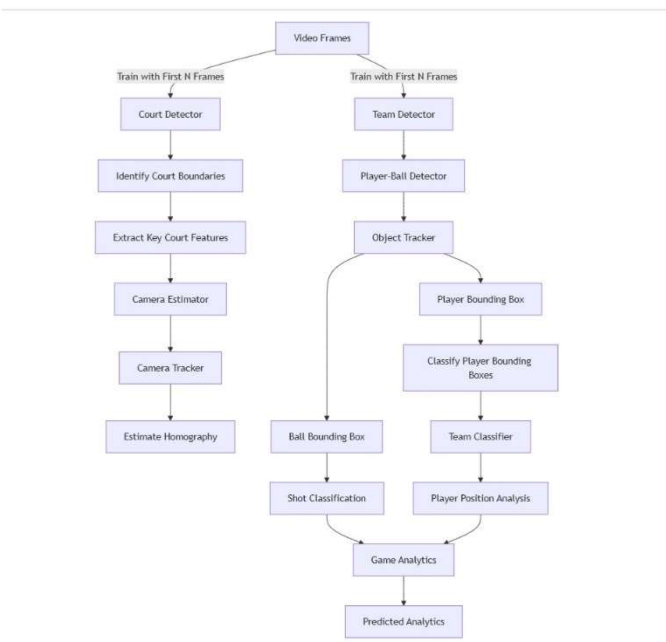

Fig. 4: Tennis workflow

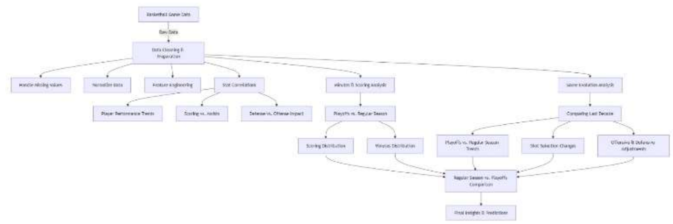

Fig. 5: Basketball workflow

A. Football Analysis Methodology: The football analysis module utilizes deep learning-based object detection and tracking techniques to analyze player movements, ball trajectory, and team strategies. The primary components of the methodology include:

1. **Data Acquisition**: The system processes football match footage, extracting frames for analysis. Videos are preprocessed to standardize frame rates and resolution to ensure uniformity.
2. **Object Detection**: The YOLO deep learning model detects players, referees, and the ball. The detections are further refined using non-maximum suppression to eliminate redundant bounding boxes.
3. **Player and Ball Tracking**: ByteTrack is implemented for multi-object tracking, assigning unique identifiers to each player and tracking their movements across frames.
4. **Tactical Analysis**: The system computes passing accuracy, possession statistics, and player heatmaps to visualize field coverage and team formations.
5. **Visualization**: A radar-style pitch representation is generated, displaying player movement paths and tactical positioning over time. The system allows analysts to examine team formations and transitions throughout the match.

B. Basketball Analysis Methodology: Unlike the football module, the basketball analysis is data-driven, focusing on player statistics rather than video tracking. The methodology consists of:

1. **Dataset Processing**: The system ingests historical player and team statistics, performing data cleaning and normalization to remove inconsistencies.
2. **Feature Selection**: Key performance indicators such as field goals, rebounds, assists, and turnovers are selected to assess player contributions.

3. **Machine Learning Models**: Logistic regression is employed to classify high-scoring players, while linear regression predicts future player performance based on past trends.

4. **Evaluation Metrics**: Precision, recall, and F1-score are computed to validate classification accuracy. The basketball model achieved a perfect 1.0 score, suggesting excellent classification but requiring further dataset expansion for generalization.

5. **Visualization and Insights**: The system generates graphs and statistical comparisons to help analysts compare players and identify top performers.

C. Tennis Analysis Methodology: The tennis analysis leverages deep learning to track player movements and ball trajectories. The methodology consists of:

1. **Frame Extraction and Preprocessing**: Video frames are extracted and resized to maintain consistency across different datasets.

2. **YOLO-Based Object Detection**: The system identifies players, court lines, and the ball. The detections are processed to classify shot types and track player movements.

3. **Shot Analysis**: Ball trajectory tracking is used to calculate shot speeds, angles, and accuracy. The system distinguishes between different types of strokes, such as forehand, backhand, and volleys.

4. **Performance Metrics**: Player agility, court coverage, and endurance are computed based on movement patterns.

5. **Visual Representation**: Movement heatmaps and shot trajectory visualizations are generated to provide insights into player strategies.

6. **D. Badminton Analysis Methodology**: Badminton is analyzed through a combination of video tracking and deep learning. The methodology includes:

1. **Model Training and Implementation**: Pre-trained models such as YOLOv8x are utilized for player and shuttlecock detection.

2. **Multi-Object Tracking**: The system implements tracking algorithms to follow the shuttlecock's motion and estimate the velocity of shots.

3. **Tactical Insights**: Metrics such as rally durations, shot distribution, and player reaction times are extracted to evaluate gameplay efficiency.

4. **Visualization Tools**: The system provides an interactive dashboard where users can assess player movements and shot accuracy trends.

E. Pool/Snooker Analysis Methodology: The pool/snooker analysis module focuses on predictive analytics for shot outcomes. The methodology involves:

1. **Table and Ball Detection**: The system processes video frames to detect table boundaries, pockets, and ball positions using color segmentation and edge detection.

2. **Shot Prediction**: The system employs trajectory estimation algorithms to predict the movement of the cue ball after impact.

3. **Physics-Based Modeling**: Motion equations and collision detection techniques are applied to forecast possible shot outcomes.

4. **Strategic Decision Assistance**: The system suggests optimal shot angles and power levels based on cue placement and ball positions.

5. **Real-Time Visualization**: A shot trajectory overlay is displayed, providing players with a visual guide for improving their accuracy.

By implementing these methodologies, this research offers an advanced AI-driven sports analytics system capable of providing statistical insights for performance evaluation. The system's modular design ensures adaptability across multiple sports while maintaining accuracy and efficiency.

IV. RESULT

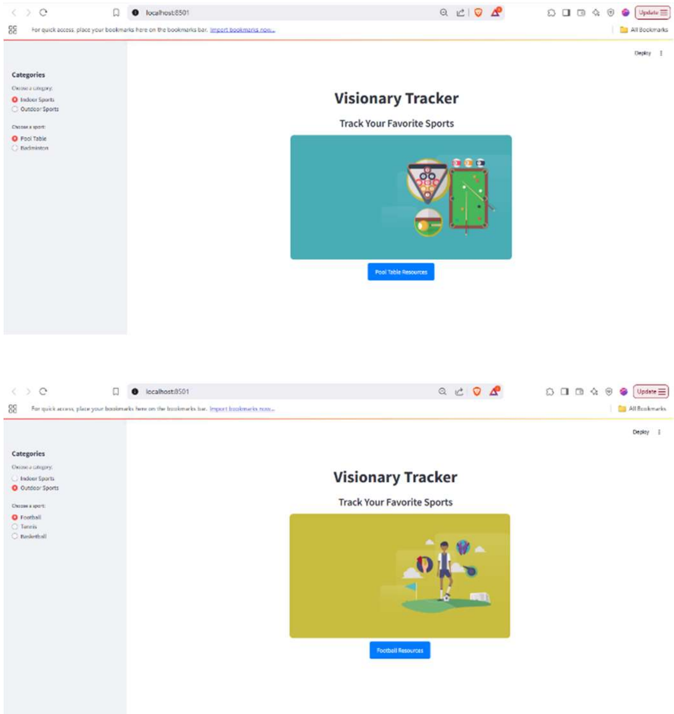

Fig. 6: Application Interface

The Visionary Tracker project successfully implemented an AI-powered platform for sports analytics. The proposed system was evaluated across multiple sports, including football, basketball, tennis, pool, and badminton. The results demonstrate the effectiveness of AI-driven sports analysis in extracting actionable insights from video and statistical data. However, the Streamlit application does not directly perform analysis or update findings; it provides drive links to each sport's code and previous results. Users must run the code in their own environment to generate new findings and conduct further analysis

V. CONCLUSION

This research presents an AI-powered sports analysis system capable of tracking players, analyzing gameplay, and providing performance insights across multiple sports. The integration of deep learning models such as YOLO and ByteTrack enables real-time object detection and tracking, while machine learning techniques enhance predictive analytics. The results demonstrate the effectiveness of the proposed system, achieving high accuracy in football, tennis, badminton, and pool/snooker analysis, while the basketball classification model achieved perfect predictive performance. However, the system does not provide real-time updates or store new analysis results; instead, it serves as a foundation for sports analysts and developers to use the provided code for their own research and development. Future improvements should focus on dataset diversity, occlusion handling, and real-time inference optimization. Enhancing tracking algorithms, integrating multi-angle video feeds, and incorporating wearable sensor data will further refine the system's capabilities. This research contributes to the advancement of AI-driven sports analytics and opens new possibilities for automated performance evaluation in competitive sports.

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