Smart Tennis Analysis

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***Abstract*—The advancement of computer vision and deep learning has enabled automated and data-driven sports analytics, particularly in tennis performance evaluation. Traditional analysis methods are manual, time-consuming, and subjective. This paper proposes an automated tennis analysis system that processes match videos to extract meaningful performance metrics. The system follows an end-to-end pipeline including frame extraction, object detection, court key point detection, object tracking, and performance analysis. Player detection is performed using YOLOv8, while tennis ball detection uses a finetuned YOLOv5 model. A convolutional neural network is used for court key point detection to map player and ball positions accurately. Tracking techniques are applied to analyze movement patterns and compute metrics such as player speed, ball speed, shot count, and distance covered. The system generates annotated videos and statistical outputs for performance evaluation. Experimental results show high accuracy in player detection and satisfactory ball detection, with minor limitations under challenging conditions. The proposed solution is cost-effective, scalable, and reduces manual effort, demonstrating the potential of AI in modern sports analytics.** **Keywords—Computer vision, Deep learning, Tennis analytics, YOLO, Performance analysis.**

I. INTRODUCTION

The growth of digital technology has changed the way sports are analyzed, moving from traditional observation methods to more intelligent and data-driven approaches. In a sport like tennis, analyzing player performance is essential for improving skills, planning strategies, and enhancing overall training. Earlier, most of this analysis was done manually by coaches or analysts, which made the process slow, subjective, and difficult to scale for large amounts of match data. As competitive sports continue to generate more data, these traditional methods are no longer sufficient. With the increasing importance of data in decision-making, there is a clear need for automated systems that can analyze gameplay more efficiently and consistently. Advances in computer vision and deep learning have made it possible to process video and data and to extract the meaningful information without manual effort. Modern object detection models such as YOLO, along with powerful deep learning frameworks, have significantly improved the ability to identify and track objects in dynamic and complex environments. However, tennis video analysis presents several practical challenges. The tennis ball is small and moves at very high speeds, making it difficult to detect consistently. In addition, variations in lighting, camera angles, and background conditions further complicate the process. In many existing systems, the focus is limited to specific tasks such as detecting players or tracking the ball, rather than providing a complete analysis pipeline. Moreover, professional systems used in tournaments often depend on specialized and expensive hardware, which limits their accessibility for general users. These challenges highlight the need for a more practical and integrated solution that can work with standard video input. The Smart Tennis Analysis System proposed in this project aims to address this requirement by combining computer vision and deep learning techniques into a unified framework. The system is designed to automatically detect players and the tennis ball using advanced object detection models. It also uses convolutional neural networks to identify important court keypoints, which helps in accurately mapping positions on the court. To ensure continuous analysis, tracking algorithms are applied to maintain the identity of players and the ball across frames. Based on this tracking data, the system calculates important performance metrics such as player movement, estimated ball speed, shot count, and overall gameplay patterns. These outputs provide useful insights that can support coaching, performance evaluation, and training decisions. The system not only reduces manual effort but also improves the consistency and reliability of analysis. It is designed to be flexible and scalable, making it suitable for different real-world scenarios without requiring expensive equipment. At the same time, certain challenges still remain, including handling motion blur, achieving real-time performance, and improving dataset quality. Addressing these issues will be important for building more accurate and efficient sports analytics systems in the future.

II LITERATURE REVIEW

This literature review synthesizes recent research in the domain of sports video analytics, computer vision, and deep learning-based performance analysis systems. It draws upon academic publications, conference proceedings, and technical reports published primarily between 2023 and 2026, focusing on advancements in object detection, tracking, and automated sports analysis. Particular attention is given to tennis analytics, where challenges such as high-speed object tracking, occlusion, and spatial mapping are critical. The review is organized thematically to mainly highlight the more technological developments, methodological approaches, limitations, and research gaps, providing a structured foundation for the proposed system. Sources have been selected totally based on relevance, recency, and applicability to real-world scenarios. The review incorporates interdisciplinary perspectives from computer vision, machine learning, and sports analytics. Emphasis is placed on understanding how existing techniques address detection, tracking, and performance evaluation, while also identifying the limitations that motivate the development of an integrated system.

2.1 Object Detection in Sports Analytics: Evolution and Challenges

Object detection is a fundamental component of sports video and analysis, enabling the identification of players, equipment, and key elements within video frames. Recent advancements in the deep learning, particularly YOLO-based architectures, have significantly improved detection accuracy and speed. Modern implementations such as YOLOv5 and YOLOv8 demonstrate strong performance in real-time environments, making them suitable for dynamic sports scenarios. From multiple perspectives:

Technical Advancements:
Deep learning models have evolved to handle complex visual environments, enabling multi-object detection with high precision. YOLO-based models are widely adopted due to their balance between speed and accuracy.

Application in Tennis:
Detection of players is relatively reliable due to their size and visibility. However, detecting the tennis ball remains challenging because of its small size, high velocity, and motion blur.

Edge Cases:
Performance degradation occurs under varying lighting conditions, occlusion, and camera movement, especially in outdoor matches. Critiques and Gaps:
Most detection models are trained on general datasets and may not generalize effectively to tennis-specific scenarios without fine-tuning.

Implications:
These challenges highlight the need for specialized models and datasets for accurate sports-specific object detection.

2.2 Object Tracking and Motion Analysis in Sports Videos

Object tracking plays a critical role in maintaining the identity of detected objects across frames and analyzing their movement over time. Recent research focuses on deep learning-based tracking algorithms that incorporate temporal information motion patterns to improve accuracy. From various analytical angles:

Tracking Techniques:
Approaches such as Kalman filtering, optical flow, and deep learning-based trackers are commonly used to track players and the ball.

Performance Insights:
Tracking enables computation of movement metrics such as speed, trajectory, and positional changes, which are essential for performance analysis.

Challenges:
Occlusion, rapid movement, and sudden direction changes can lead to tracking failures or identity switching.
Critiques and Gaps:
Many tracking systems perform well in controlled environments but struggle in real-world match conditions with complex dynamics.

Implications:
Robust tracking systems are required to ensure continuity and reliability in analysis across diverse scenarios.

2.3 Court Keypoint Detection and Spatial Mapping
Court keypoint detection is essential for mapping player and ball positions relative to the playing area. Recent studies utilize convolutional neural networks to detect court boundaries and reference points, enabling accurate spatial analysis.

From multiple viewpoints:
Technical Approaches:
CNN-based models are used to identify keypoints such as baselines, sidelines, and service lines.

Importance in Analysis:
Accurate keypoint detection allows for precise calculation of distance covered, positioning, and movement patterns.

Challenges:
Variations in camera angles, shadows, and court conditions can affect detection accuracy. Critiques and Gaps:
Limited availability of annotated datasets for court keypoints reduces model generalization.

Implications:
Improved datasets and robust models are required for reliable spatial mapping in real-world conditions.

III. COMPARISON WITH EXISTING USE CASE FOR TENNIS

Existing sports analytics systems and tools provide various techniques for performance evaluation in tennis; however, they often lack real-time, automated, and cost-effective solutions. This section compares commonly used approaches with the proposed Smart Tennis Analysis system to highlight current limitations.

3.1. Hawk-Eye System
The Hawk-Eye system is widely used in professional tennis tournaments for ball tracking and line judgment. It provides highly accurate trajectory predictions using multiple high-speed cameras. However, the system is extremely expensive, requires specialized hardware setup, and is not accessible for general users, coaches, or amateur players.

3.2. Wearable Sensor-Based Systems
Wearable devices such as smart rackets and motion sensors track player movements, swing speed, and impact data. While these systems provide useful insights, they depend on additional hardware and may not capture full gameplay context like ball trajectory or opponent positioning. They also introduce inconvenience for users due to device dependency.

3.3. Manual Video Analysis
Traditional video analysis involves recording matches and manually reviewing footage to extract insights. Coaches analyze player movement, shot selection, and errors frame by frame. Although effective, this method is time-consuming, subjective, and lacks automation, making it inefficient for large-scale or real-time analysis.

3.4. Generic Computer Vision Models
Some research and open-source projects use computer vision techniques for sports analytics. These systems often detect players or objects using models like YOLO (You Only Look Once) and Convolutional Neural Networks. However, many of these implementations are not fully integrated, lack domain-specific tuning for tennis, and do not provide complete metrics such as shot speed or rally statistics.

3.5. Commercial Sports Analytics Software
Commercial tools offer performance tracking and match statistics but are usually subscription-based and designed for professional teams. They often lack flexibility, transparency in algorithms, and customization for type of individual users and the academic purposes. Additionally, limited access to underlying models restricts experimentation and

innovation in research environments. Hence, there is a growing demand for flexible and transparent systems that support academic and individual use.

Proposed Advantage of Smart Tennis Analysis
Unlike existing systems, the proposed Smart Tennis Analysis project introduces a fully automated, vision-based approach that utilizes advanced deep learning and computer vision techniques to analyze tennis gameplay directly from video input in a seamless and efficient manner. The system leverages models such as YOLO (You Only Look Once) for efficient object detection and Convolutional Neural Networks (CNNs) for accurate court keypoint extraction and spatial understanding. Through this integrated and intelligent approach, the system is capable of automatically detecting players and the tennis ball with high precision, thereby completely eliminating the need for manual intervention and reducing the human effort. Furthermore, the proposed system enables precise measurement of player movement speed and ball shot speed by analyzing frame-by-frame positional changes over time. It also facilitates tracking of shot count, rally duration, and identification of complex rally patterns, which are essential for in-depth performance evaluation and strategic analysis. In addition, the detection of court keypoints ensures accurate spatial mapping, allowing the system to interpret player positioning, shot placement, and movement dynamics effectively within the defined court boundaries. Here The system further incorporates temporal analysis techniques to understand player behavior over extended rallies, enabling the identification of strengths, weaknesses, and performance trends. It can also assist in detecting key events such as serves, volleys, and baseline shots, providing a more detailed breakdown of gameplay. By utilizing efficient data processing pipelines, the system ensures that analysis can be performed with minimal latency, making it suitable for near real-time feedback. Additionally, the modular design of the system allows easy integration with other analytical tools and platforms for enhanced functionality. The use of deep learning models also enables continuous improvement in accuracy as more data becomes available, making the system adaptive over time. A major sort significant advantage of this approach is that it does not require expensive hardware setups or wearable sensor devices, making it highly accessible, scalable, and cost-effective compared to traditional solutions currently used in professional sports analytics. The system is designed to be flexible and adaptable across different playing conditions, allowing it to be used by a wide range of users, including players, coaches, analysts, and researchers. By combining automation with near real-time analytical capabilities, the Smart Tennis Analysis system significantly enhances the efficiency, accuracy, and practicality of performance evaluation while ensuring easy deployment in real-world scenarios.

IV. PROJECT OBJECTIVES

The primary objective of the proposed Smart Tennis Analysis System is to design and develop an intelligent, automated framework capable of analyzing tennis match videos using computer vision and deep learning techniques. The system aims to bridge the gap between traditional manual analysis and modern data-driven approaches by providing a scalable, accurate, and efficient solution for extracting meaningful insights from video

4.1 To Develop an Automated Tennis Video Analysis System
One of the fundamental objectives of this project is to eliminate the dependency on manual observation by introducing an automated system capable of processing tennis match videos. Traditional analysis methods require significant human effort and are often subjective in nature, leading to inconsistencies in evaluation. The proposed system aims to automate the entire workflow, starting from video input to performance analysis, thereby reducing human intervention and improving efficiency. The system is designed to process video data in a structured manner, ensuring that all relevant information is captured and analyzed. By automating tasks such as detection, tracking, and metric computation, the system enables faster and more reliable analysis compared to conventional methods. This objective is particularly important in scenarios where large volumes of video data need to be analyzed within limited time.

4.2 To Implement Accurate Player and Ball Detection Using Deep Learning
Another key objective of the project is to achieve accurate detection of players and the tennis ball using

advanced deep learning models. Object detection forms the foundation of the entire system, as all subsequent stages depend on the correctness of detected objects. The system utilizes YOLO-based models to identify players and the tennis ball with in video frames. While player detection is relatively straightforward due to the size and visibility of players, tennis ball detection presents unique challenges because of its small size and high velocity. The objective is to design a detection mechanism that can handle these challenges effectively and provide reliable results across different match conditions. Achieving high detection accuracy ensures that the system can perform robust analysis and generate meaningful insights without significant errors.

4.3 To Enable Continuous Object Tracking and Motion Analysis

Tracking is an essential component of the system, and a major objective is to ensure consistent and reliable tracking of players and the tennis ball across frames throughout the entire video sequence. The system aims to maintain object identity over time, enabling continuous and uninterrupted analysis of movement patterns without losing contextual information. By implementing robust and efficient tracking mechanisms, the system can generate accurate trajectories for both players and the ball. These trajectories are crucial for understanding gameplay dynamics and for calculating important performance metrics such as speed, direction, acceleration, and total distance covered during rallies. Additionally, maintaining stable tracking allows the system to analyze temporal patterns, such as player positioning trends and shot transitions, which contribute to deeper strategic insights. The objective is to minimize tracking errors such as identity switching, detections, and loss of objects during rapid movements or occlusions, as these issues can significantly affect the accuracy and reliability of the analysis. Advanced techniques are incorporated to improve tracking stability even in challenging scenarios. The proposed methodology combines these components into a unified detection, tracking, and analysis modules. This integrated approach enables the system to process raw video data and transform it into structured, meaningful insights in a seamless and efficient manner. Furthermore, the methodology is designed to handle practical challenges such as fast-moving objects, partial or full occlusion of players, camera motion, and variations in lighting conditions, all of which are common in real-world tennis match videos. This makes the system robust, dependable, and suitable for practical deployment across different environments.

V. METHODOLOGY

This section presents the methodological framework adopted for the design and development of the Smart Tennis Analysis System. The methodology focuses on integrating computer vision and deep learning techniques into a structured pipeline capable enough to of analyze the tennis match videos and extracting meaningful performance metrics. The approach emphasizes practical implementation, system scalability, and adaptability to real-world conditions, ensuring that the system remains effective across different environments and video qualities. Unlike traditional systems that treat detection, tracking, and analysis as independent tasks, the proposed methodology combines these components into a unified workflow. This integrated approach enables the system to process raw video data and generate structured insights in a seamless manner. The methodology is designed to handle challenges such as fast-moving objects, occlusion, and variations in lighting conditions, which are common in tennis match videos.

5.1 Research Approach and Methodological Framework

The project adopts a good design-oriented applied research methodology, focusing on the development of a functional and scalable system for tennis video analysis. The approach is constructive in nature, aiming to translate theoretical concepts from computer vision and machine learning into a working solution that addresses real-world challenges. Rather than proposing new algorithms, the methodology leverages existing deep learning models and adapts them for tennis-specific applications. The focus is on system integration, where detection, tracking, and analysis modules are combined into a single pipeline. This approach ensures that the system is both practical and efficient, capable of producing reliable results without excessive computational complexity. The research also considers usability and deployment aspects, ensuring that the system can operate on standard video input without requiring specialized equipment.

Fig. 1. Smart tennis analysis picture analyzing players movement.

5.2 System Architecture Design

The proposed system follows a modular and layered architecture that allows different components to operate independently while contributing to the overall workflow. This design improves maintainability and allows individual modules to be updated or replaced without affecting the entire system.

The architecture consists of the following key layers

Input and Preprocessing Layer:

Handles video input and converts it into frames. Preprocessing ensures that frames are compatible with detection models.

Detection Layer:

Identifies players and the tennis ball using deep learning models. YOLOv8 is used for player detection, while a finetuned YOLOv5 model is used for tennis ball detection.

Spatial Mapping Layer:

Detects court keypoints using convolutional neural networks, enabling accurate mapping of object positions within the court.

Tracking Layer: Maintains object identity across frames, enabling continuous motion analysis.

Analysis Layer:

Computes performance metrics based on tracked data.

Output Layer:

Generates annotated video and statistical results.

This layered architecture ensures a clear flow of data and improves system reliability.

5.3 Court Keypoint Detection and Spatial Mapping

To provide meaningful context to detected objects, the system performs court keypoint detection. This involves identifying important court boundaries such as baselines, sidelines, and service lines. A convolutional neural network is used to detect these keypoints. Once detected, the keypoints are used to establish a coordinate system for the court. This allows the system to map object positions accurately within the playing area. Spatial mapping is essential for calculating performance metrics such as distance covered and positioning. It ensures that all measurements are consistent and meaningful.

5.4 Object Tracking and Motion Analysis

Tracking is performed to maintain object identity across frames and analyze movement over time. The tracking module associates detected objects in consecutive frames based on their position and motion. This stage generates continuous trajectories for players and the tennis ball. These trajectories are used to analyze movement patterns, speed, and interactions. Tracking also helps in handling temporary detection failures by maintaining object identity even when objects are briefly occluded.

5.5 Performance Metric Computation

The performance metric computation stage focuses on turning raw tracking data into useful insights about the game. After the system tracks the positions of players and the tennis ball across video frames, this module processes that information to calculate meaningful performance indicators. These metrics help in understanding how players move, how fast the game progresses, and how different actions influence overall performance. A key metric calculated is player movement speed. This is obtained by measuring how much a player's position changes between consecutive frames and then converting that movement into real-world distance using the court's spatial mapping. In a similar way, the speed of the tennis ball is estimated by tracking its motion across frames and computing how quickly it travels over time. Frame rate and scaling factors are carefully considered so that the results remain realistic and consistent. Apart from speed, the system also identifies and counts the number of shots in a rally. This is done by analyzing how the ball changes direction and how close it gets to each player, which helps in detecting when a shot occurs. By following this pattern over time, the system can also recognize rally sequences and their duration. This provides a better understanding of gameplay intensity and how players respond during exchanges. To make the results more reliable, the system includes steps to reduce noise and handle small errors in detection. Techniques such as smoothing and filtering are applied so that sudden fluctuations do not affect the final output. As a result, the computed metrics are stable and can be confidently used for evaluating performance or comparing different matches.

5.6 Output Generation and Visualization

The final stage of the system focuses on presenting the analysis results in a way that is easy to understand and visually clear. Instead of just producing raw numbers, the system combines the computed data with the original video to generate an annotated output. This makes it easier for users to directly see how the analysis relates to actual gameplay. During this process, visual elements are added to each frame of the video. These include bounding boxes around players and the tennis ball, as well as trajectory lines that show movement paths. Key performance metrics such as player speed, ball speed, and shot count are also displayed in real time, allowing users to follow the analysis as the video plays. Along with the visual output, the system generates a summary of important statistics from the match. This may include average player speed, maximum ball speed, total number of shots, and rally durations. These summaries give a quick overview of the match and can be used for further evaluation or reporting purposes. The design of this module keeps usability in mind. The goal is to ensure that even someone without a technical background can understand the results easily. By combining visual cues with numerical data, the system makes performance insights more accessible and practical. Additionally, the output can be saved and shared, which allows users to review gameplay later or compare performances over multiple sessions. Overall, this module plays an important role in making the system useful in real-world scenarios by converting complex analysis into clear and actionable information.

VI. PRELIMINARY DATA ANALYSIS AND PERFORMANCE EVALUATION

This section presents the preliminary analysis of the data used in the Smart Tennis Analysis System and evaluates the system’s performance under different conditions. The objective of this analysis is to understand how effectively the system processes tennis video data, how reliable the detection and tracking components are, and how meaningful the generated performance metrics are in practical scenarios. Unlike large-scale deployed systems, the evaluation in this project is conducted using controlled experiments and sample tennis match videos. The analysis focuses on qualitative and functional performance rather than extensive statistical benchmarking, while still providing insights into system behavior and limitations.

6.1 Dataset Characteristics and Input Variability

The system is tested using a combination of real-world tennis match videos and sample datasets. These videos vary in resolution, frame rate, camera angle, and lighting conditions, providing a realistic evaluation environment.

Key characteristics of the dataset include:
Variability in video quality (high-resolution and low-resolution inputs) Differences in camera positioning (top view, side view, broadcast view) Presence of motion blur during fast rallies Background with complexity including audience and court surroundings. This diversity ensures that the system is evaluated under conditions that closely resemble real-world scenarios rather than ideal laboratory settings.

6.2 Detection Performance Analysis

The detection module is evaluated based on its ability to correctly identify players and the tennis ball across frames.

Player Detection:
The YOLOv8 model demonstrates high accuracy in detecting players due to their relatively large size and distinct features. Detection remains stable across different lighting conditions and camera angles.

Tennis Ball Detection:
The fine-tuned YOLOv5 model performs reasonably

well in detecting the tennis ball. However, occasional missed detections are observed during high-speed motion or when the ball is partially occluded. Despite these challenges, the model maintains acceptable performance for analysis purposes.

Observations:
Detection accuracy is higher in well-lit conditions and decreases slightly in low-resolution or blurred frames.

6.3 Tracking Performance Evaluation

The tracking module is analyzed based on its ability to maintain object identity across frames and generate consistent trajectories. In. The system successfully tracks player movement across frames with minimal identity switching. Ball tracking shows good continuity in moderate-speed scenarios but may experience interruptions during extremely fast shots. The tracking mechanism effectively bridges temporary detection gaps, improving overall system stability.

VII. FUTURE ENHANCEMENTS

While the proposed Smart Tennis Analysis System demonstrates the feasibility of automated sports video analysis using computer vision and deep learning techniques, there are several areas where the system can be further improved and extended. These enhancements focus on increasing accuracy, improving usability, enabling real-time performance, and expanding the scope of analysis.

7.1 Enhancement of Tennis Ball Detection Accuracy

One of the most noticeable limitations in the current system is the difficulty in consistently detecting the tennis ball, especially during high-speed rallies or under motion blur conditions. Future improvements can focus on training the detection model using larger and more diverse datasets specifically designed for small object detection. Advanced architectures that specialize in detecting small and fast-moving objects can also be explored. Additionally, incorporating temporal information across frames rather than relying solely on individual frame detection may significantly improve detection consistency.

7.2 Real-Time Processing and Optimization

At present, the system processes videos in an offline manner, which limits its applicability in live match scenarios. A major area of enhancement is enabling real-time analysis by optimizing the system for faster inference. Techniques such as model pruning, quantization, and GPU acceleration can be used to reduce computational overhead. Deploying the system using optimized frameworks can further improve processing speed, making it suitable for live sports analytics. In addition to hardware-based optimizations, algorithmic improvements play a crucial role in enhancing system efficiency. Techniques such as frame skipping and region-of-interest (ROI) based processing can significantly reduce unnecessary computations by focusing only on relevant areas within each frame. This helps maintain detection accuracy while improving processing speed. Another important approach involves optimizing the model architecture itself. Lightweight versions of object detection models, such as YOLO-tiny variants, can be employed to achieve faster inference with minimal compromise in accuracy. Batch processing and parallel execution using multi-threading can further enhance performance, especially when handling continuous video streams. Memory management is also a key factor in real-time systems. Efficient handling of intermediate data and minimizing redundant storage operations ensure smoother execution and prevent system slowdowns. Additionally, leveraging modern APIs and optimized libraries can improve overall system responsiveness.

VIII. CONCLUSION

The Smart Tennis Analysis System presents a practical and effective approach to automating tennis video analysis using computer vision and deep learning techniques. The system successfully integrates multiple components, including video processing, object detection, court keypoint detection, tracking, and performance analysis, into a unified pipeline. One of the key contributions of this work is the development of an end-to-end system that can process raw video input and generate meaningful insights without requiring manual intervention. The use of YOLO-based models for object detection enables efficient identification of players and the tennis ball, while tracking mechanisms ensure continuity across frames. The incorporation of court keypoint detection further enhances the accuracy of spatial analysis.

System is capable of generating useful performance metrics such as player movement, ball speed estimation, shot count, and positional patterns. These metrics provide valuable insights into gameplay and can be used for performance evaluation, coaching, and training. The experimental results demonstrate that the system performs reliably under normal conditions, achieving high accuracy in player detection and satisfactory performance in tennis ball detection. While certain limitations exist, particularly in handling motion blur and real-time processing, the overall system performance is strong and demonstrates the feasibility of automated sports analytics. From a broader perspective, this project highlights the growing importance of artificial intelligence in sports. By transforming traditional analysis methods into automated, data-driven processes, the system contributes to improving efficiency, accuracy, and accessibility in sports analytics.

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