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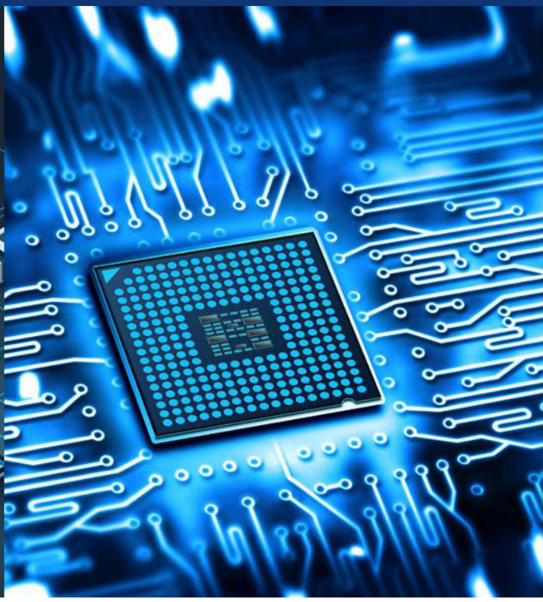

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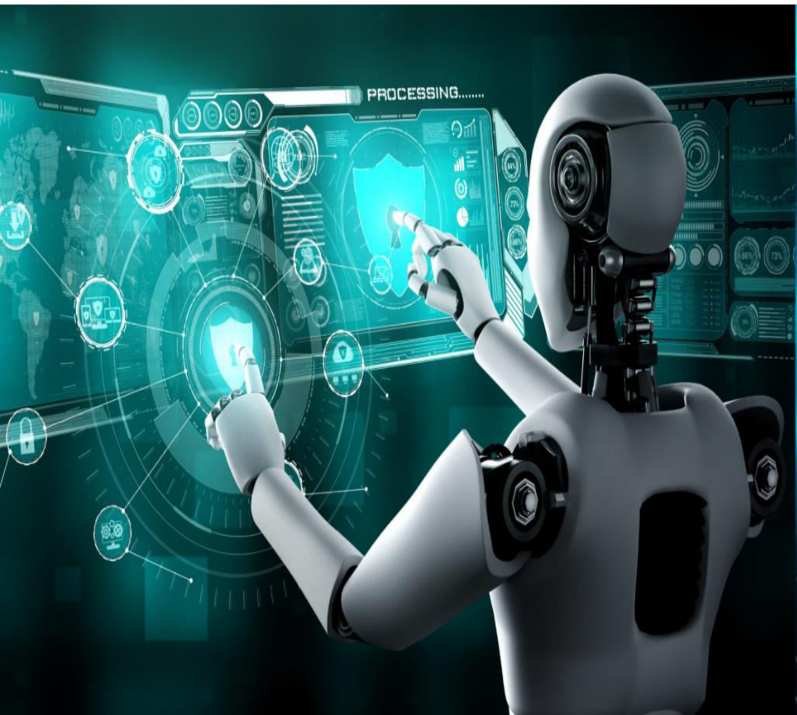

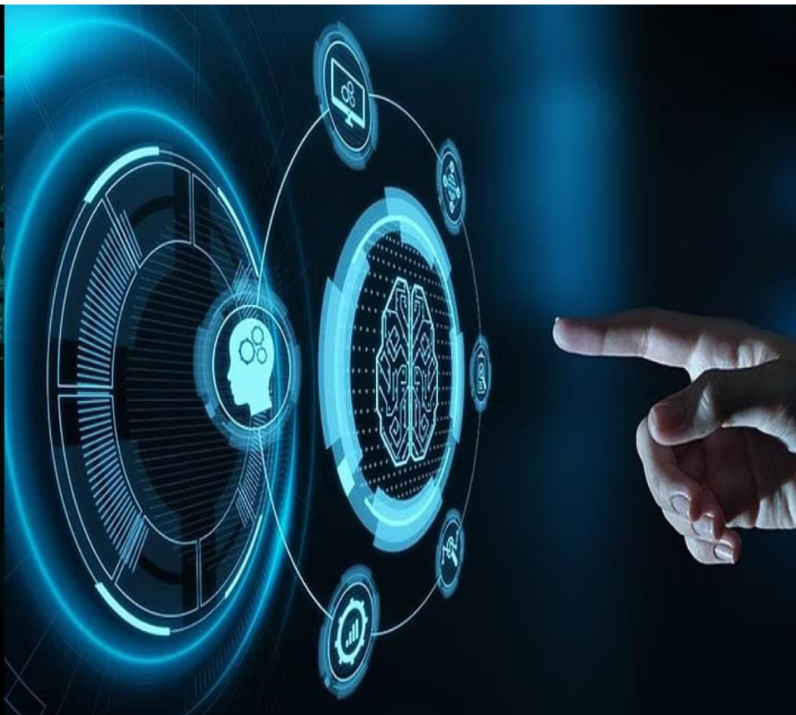

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Football Analysis System using Machine Learning

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ABSTRACT: Football creates a considerable amount of data, but classical ways of analyzing is often unable to encapsulate the intricacies of the game. This research presents the development of an integrated football analysis system which is based on advanced technologies to overcome these challenges. Players and referees' activities and the ball's motion in the field are real time detected and tracked with the application of YOLO algorithm no matter how fast the action is. Additionally, it incorporates K-Means segmentation for the player, optical flow analysis for motion tracking the camera, and perspective projection for the precise metrics of the player movements. This approach provides in-depth understanding of players and team activities, enabling coaches and analysts to apply these insights in practice in a fast manner.

KEYWORDS: YOLO, K-Means, segmentation, metrics, football analysis

I. INTRODUCTION

Football is unquestionably the most popular sport in the world and possesses enormous information that can transform the assessment of both a player and a team's performance. Historical approaches have been inadequate to measure the complexity and the speed of the modern rhythm of a football match, to say the least. To overcome these deficits, a highly described football analysis system is now available, incorporating information such as the use of YOLO image recognition for real time object detection, K-Means clustering for the segmentation of players and optical flow for the movement of the camera. When these methods are used together with perspective transformation methodologies, it allows to accurately quantify the players' actions and team tactics as well as the performance of the whole game, which could be of great help to coaches, analysts and the fans.

In addition to these advanced techniques, the system also integrates machine learning models to predict player movements, identify patterns in team formations, and analyze strategic plays. By training a custom YOLO object detector, it enhances accuracy in distinguishing players, referees, and the ball, even in complex scenarios. Furthermore, the use of optical flow not only aids in detecting camera movement but also assists in tracking player trajectories across frames, enabling precise measurement of speed and distance covered. Such insights, combined with detailed data visualization, provide an unparalleled depth of analysis, empowering teams to refine their strategies and gain a competitive edge.

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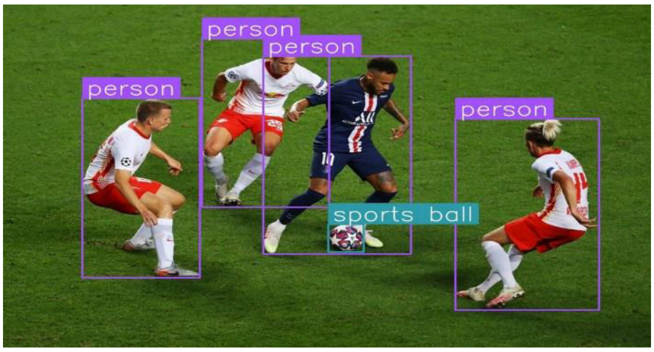

Figure 1 Players of two different teams and the football detected each team player and football shown in different colored rectangular box

II. LITERATURE SURVEY

[1] Tanvir Ahmad present an improved YOLOv1 model for object detection. Their approach integrates inception modules, which allow for parallel processing of different sized convolutions, and incorporates proportional loss functions. These modifications aim to enhance the model's ability to identify objects accurately and efficiently.

[2] Gudala Lavanya Sagar Dhanraj Pande Gudala Lavanya highlighted the advancements in real-time object detection, specifically focusing on the evolution of the YOLO architecture. They discuss the significant impact of YOLO and its subsequent versions on various applications, including video surveillance and robotics, where real-time detection is crucial.

[3] Shankara Narayanan et al. Shankara Narayanan et al. utilize refined versions of YOLO and BYTETrack to track players and analyze ball possession during football matches. This research demonstrates the potential of deep learning techniques in sports analytics, enabling more accurate and insightful analysis of player movements and game dynamics.

[4] K. Vaishnavi et al. address the challenge of real-time tracking of small objects. They propose enhancements to the Single Shot Detector (SSD) model by incorporating advanced convolutional techniques. These improvements aim to boost the accuracy and reliability of the SSD model in tracking small objects, which is critical in various applications.

[5] Licheng Jiao et al. Licheng Jiao et al. offer a comprehensive review of deep learning algorithms, with a particular focus on object detection. They analyze the advancements in object detection techniques and explore their diverse applications across various domains. This review provides a valuable overview of the current state-of-the-art in deep learning-based object detection.

[6] G.A. Thomas G.A. presents an innovative approach to real-time camera tracking in sports broadcasting. By utilizing pitch markings as a reference, the propose

III. EXISTING SYSTEM

The existing systems for football performance analysis focus heavily on leveraging technology to capture, track, and analyze player and ball movements during matches. However, they often come with several challenges such as high costs, reliance on complex infrastructures, and manual data entry. Below is a detailed exploration of some of the key existing systems that have been deployed to capture and analyze football data, their features, and limitations..

A Opta Sports

• **Overview**: Opta Sports is a renowned provider of sports data, specifically focused on football. It offers comprehensive insights into player performance metrics, match statistics, and tactical analysis.

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- **Features:**
- Extensive data coverage across global football leagues and competitions.
- Real-time and historical match event data, such as passes, tackles, shots, assists, etc.
- Advanced tools for visualizing and analyzing player performance.
- Metrics for team performance and strategic insights for coaches and analysts.
- Supports both manual data collection and automated tools for real-time analysis.

- **Limitations:**
- Manual Data Entry: Despite some automation, a significant portion of the data still requires human input, making it prone to errors and inconsistencies. This process is time-consuming and can lead to delays in real-time performance analysis.
- High Costs: Opta's services come with a high price tag, making it out of reach for smaller clubs, amateur teams, or individual analysts without a significant budget.
- Complexity: The vast array of data and analysis tools may require specialized knowledge to fully understand and utilize the system, which can make it difficult for non-expert users.

B Stats Perform

- **Overview:** Stats Perform is a leading sports analytics company that provides teams, broadcasters, and media outlets with detailed performance insights. Their platform is powered by advanced data collection technologies, AI, and machine learning to analyze player movements and in-game events.

- **Features:**
- AI and Machine Learning Integration: Uses algorithms to provide predictive analytics, including performance forecasts, player impact ratings, and tactical insights.
- Comprehensive Data: Offers detailed statistics on player and team performance, such as ball possession, passes completed, shots on target, and much more.
- Video and Scouting Reports: Includes video analysis tools that allow users to review matches and gain tactical insights.
- Real-Time Data: Provides in-game analytics and performance tracking that can be used for live decision-making by coaches and analysts.

- **Limitations:**
- High Expense: Similar to Opta, Stats Perform is expensive, making it inaccessible for smaller clubs and amateur teams, especially considering the range of advanced services and technology required.
- Complex Infrastructure: To fully leverage Stats Perform's tools, teams need to invest in sophisticated infrastructure, data storage, and processing capabilities. This is a barrier for many smaller entities.
- Expertise Required: The platform requires a certain level of expertise to use effectively, limiting its accessibility for casual users or teams without dedicated analysts.

C STATSports

- **Overview:** STATSports is a provider of GPS-based performance tracking technology, specifically designed for elite sports teams. Its systems are widely used in football for tracking player movements, analyzing physiological performance, and assessing workload during both training sessions and matches.
- **Features:**
- GPS and Wearable Technology: Players wear GPS devices that track metrics like distance covered, speed, heart rate, and other key physiological parameters.
- Real-Time Feedback: Coaches and analysts receive live data on player performance, allowing for immediate adjustments and strategic insights.
- Cloud-Based Platform: The data is synced to the cloud for easy access and analysis. This enables teams to monitor performance remotely.
- Workload and Recovery Insights: The system helps coaches monitor players' workload and recovery, ensuring optimal physical conditioning.
- Limitations:

- Training Focused: While STATSports is excellent for training sessions, its applicability to matchday performance analysis is limited. It's not always possible to use the wearable devices during live matches, especially in high-intensity situations.
- Cost: The system is expensive, with high upfront costs for wearable devices and ongoing maintenance, making it prohibitive for smaller or less wealthy clubs.
- Limited Object Detection: The system lacks advanced capabilities for precise ball and player tracking during matches, limiting its application for detailed matchday analysis.
- Not Always Real-Time in Match Conditions: The real-time feedback may not be as accurate or detailed during actual games due to various environmental and logistical challenges.

D Hawk-Eye Innovations

• **Overview**: Hawk-Eye is a well-known optical tracking technology provider used in various sports for performance analysis, including football. It is primarily used for officiating purposes (such as goal-line technology and VAR) but also provides valuable insights into player and ball movements.

• **Features:**
- High Precision: Hawk-Eye offers highly accurate tracking of both player and ball movements, with real-time synchronization of video feeds and data.
- Goal-Line Technology: One of its key applications is in goal-line technology, where it provides precise information on whether the ball has crossed the line.
- Video Assistant Referee (VAR): Hawk-Eye's technology is integral to VAR systems, allowing for detailed video reviews of key match events (e.g., goals, offside decisions, penalty calls).
- Real-Time Data Synchronization: The system provides immediate data and video feeds to referees, broadcasters, and coaches.

• **Limitations:**
- Extremely High Cost: The implementation of Hawk-Eye technology is expensive, often only affordable for top-tier leagues and large-scale tournaments.
- Complex Installation: The system requires a complex installation process, including cameras and sensors positioned around the stadium. This can be logistically difficult and costly.
- Limited Scope: While Hawk-Eye is excellent for tracking specific events like ball crossing the goal line or VAR reviews, its usage for general football performance analysis (e.g., player movements, tactical insights) is less widespread.

IV. PROPOSED SYSTEM

This section presents the methodology for developing and assessing the Football analysis system using machine learning. In addition, it describes its experimental setup design.

Proposed System

The proposed system is designed to analyze football video footage and extract key insights such as player and ball positions, team assignments, and camera movement. The system uses several components working together to process the video, track players and objects, and provide metrics like speed, distance, and ball possession. Below is a detailed overview of the key components in the system, which performs tasks like object tracking, team assignment, speed estimation, ball tracking, and more.

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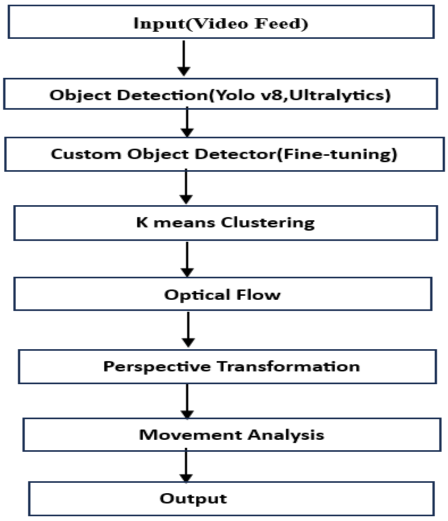

Figure 2 Architectural diagram showing the step by step process of Football Analysis System.

1. Input (Video Feed):
The system relies mainly on the input video feed for data. This is the real-time or recorded video feed of the football match, capturing all the actions on the field, such as players, referees, and the ball. The quality and resolution of this video feed significantly affect the accuracy of the analysis that follows. High-definition cameras are used in most cases to ensure clear visibility, which helps detect subtle movements and interactions during the game.
Video also feeds in as a continuous stream of information, then segmented into individual frames for analysis. This creates a snapshot view of the game, which the system uses for processing dynamic changes in player movement, ball movement, and team formation. This level of data forms the foundation for more advanced analytical techniques, such as object detection, motion tracking, and tactical evaluation.

2. Object Detection (YOLO v8, Ultralytics):
The YOLOv8 is one of the top-edge object detection models that is actually processing an image or video frames in real-time. It identifies and categorizes all the most key objects - like players, referees, or a ball, doing it exceptionally fast and precise. Its efficiency especially fits football analysis well, in which quick, and precise detection can capture very fast action on the field. The system, utilizing YOLO v8, thereby ensures that no critical event will be overlooked in terms of a player's dribble, a referee's decision, or the movement of the ball while the match is going on. Due to its ability to handle complex scenes like overlapping players or partial occlusions during analysis, the model is reliable even for challenging scenarios. The real-time detection capability is very important for applications like live match analysis and strategic decision-making.

3. Custom Object Detector (Fine-Tuned):
In addition to this, a finetuned custom object detector is implemented to further refine object detection and increase its accuracy. This includes using the YOLO model with datasets annotated on diverse football scenarios, such as lighting conditions, various uniforms worn by players, and interference from the crowd. Fine-tuning this model will enable it to perform correctly in difficult environments specific to football analysis. This customization allows the detector to recognize objects and scenarios that generic models might overlook. For example, it can differentiate between players on the same team or identify unique events like a ball going out of play. By tailoring the model to the specific needs of football analysis, the system achieves a higher level of precision, making it an invaluable tool for coaches and analysts.

4. K-Means Clustering:
K-Means clustering is a machine learning technique used to segment players into distinct groups based on visual features, such as t-shirt colors. In the context of football analysis, this method helps classify players into their respective teams by analyzing pixel values in the video frames. The clustering algorithm groups similar pixels together, effectively distinguishing between players of different teams.This segmentation process is important to understand team

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formations, tactics, and interactions while playing. For instance, it enables the system to map the positioning of each team on the field, which reveals their defensive or offensive strategies. K-Means clustering thus automates the classification process with much reduced manual effort and higher accuracy in the analysis of the teams.

5. Optical Flow:
It refers to the computer vision technique that helps to track the motion of objects in consecutive frames of a video. It is used dually in football analysis: the motion of the players, the referees, and the ball as well as detecting camera movement. Optical flow measures the direction and magnitude of motion that provides valuable data on player trajectories and interactions.This technique is particularly useful for dynamic analyses, such as measuring the speed of a player's sprint or the ball's trajectory after a kick. It also helps identify off-the-ball movements that are critical for understanding team strategies. Furthermore, optical flow aids in stabilizing the analysis when the camera moves, ensuring consistent tracking and accurate measurements.

6. Perspective Transformation:
This data combination by optical flow and perspective transformation analysis gives detailed insight into the player and ball movement. It further involves the calculation of metrics such as speed, distance covered, and changes in direction. The tracking of these dynamics provides a detailed understanding of an individual's performance as well as a team's during the game.

7. Movement Analysis:
Movement analysis combines data from optical flow and perspective transformation to provide detailed insights into player and ball movements. This includes calculating metrics such as speed, distance covered, and changes in direction. By tracking these dynamics, the system offers a comprehensive understanding of individual and team performance during the game. This analysis is invaluable for evaluating player fitness, understanding tactical execution, and identifying areas for improvement. For example, it can highlight the most active players on the field or measure how effectively a team transitions between attack and defense. Movement analysis transforms raw motion data into actionable insights, aiding decision-making for coaches and analysts.

8. Output:
The final output of the system is a detailed and user-friendly analysis of the football match. This includes metrics like player movements, team formations, ball trajectories, and tactical insights. The results are typically presented through visual dashboards, annotated video overlays, or interactive reports, making it easy for coaches, analysts, and fans to interpret the data. By providing a clear and comprehensive view of the game, the output enables informed decision-making and strategic planning. Coaches can refine their tactics, analysts can identify patterns and trends, and fans can gain a deeper appreciation of the game. The system's output bridges the gap between raw data and meaningful insights, making football analysis more accessible and impactful.

V. IMPLEMENTATION

This section outlines the practical implementation of the football analysis system, highlighting the algorithms, models, tools, and methods used to achieve real-time player tracking, ball possession measurement, team assignment, and detailed movement analysis. The system leverages cutting-edge machine learning models, such as YOLOv8, K-Means clustering, and optical flow, to create a robust and efficient solution for football performance analysis.

1. System Architecture and Components
The football analysis system comprises several key components: video input preprocessing, object detection, object tracking, team assignment, ball tracking, movement analysis, and result visualization. The system integrates these components to analyze football matches, offering coaches, analysts, and enthusiasts valuable insights into player performance, team tactics, and game dynamics.

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2. Implementation Details

A. Input Video Feed Preprocessing

1. Data Collection: The system takes raw video footage from cameras placed around the football field. These videos are either recorded or streamed in real-time during a match. The video feed is typically provided in formats such as MP4 or AVI for easy compatibility with the system.
2. Frame Extraction: The video is processed frame-by-frame. Each frame represents a snapshot of the match, which is then used for object detection and tracking.

- The frames are resized to a standard size to ensure uniform processing across various video resolutions.
- The pixel values of the frames are normalized to enhance detection accuracy.

3. Frame Preprocessing: The frames are processed to highlight features such as player silhouettes, the ball, and the pitch boundaries. This is crucial to improve the effectiveness of object detection algorithms.

B. Object Detection using YOLOv8

1. YOLOv8 Model: The YOLOv8 model, provided by Ultralytics, is a state-of-the-art object detection model trained to identify players, referees, and the football within each frame. YOLOv8's real-time performance is essential for accurately detecting fast-moving objects in football games.

- Model Training: A pre-trained YOLOv8 model is fine-tuned with football-specific datasets containing annotated images of players, balls, and referees under various conditions. This dataset accounts for different lighting conditions, uniforms, and partial occlusions during the match.
- Detection: Each frame is fed into the YOLOv8 model, which outputs bounding boxes around detected objects (players, referees, and the ball), along with class labels and confidence scores.

2. Model Execution:

- Step 1: The YOLOv8 model is loaded into the system, using pre-trained weights for object detection.
- Step 2: Each frame from the video feed is passed through the model.
- Step 3: The system extracts and stores the bounding boxes, labels, and confidence scores for each object detected in the frame.

C. Object Tracking

1. Tracking Algorithm: After object detection, an object tracking algorithm, such as SORT (Simple Online and Realtime Tracking) or Deep SORT (which integrates appearance features for better tracking), is used to track the movement of the players and the ball across frames.

- Step 1: The tracker is initialized with the bounding boxes from the object detection step.
- Step 2: The tracker continuously updates the positions of the tracked objects across the frames.
- Step 3: The unique IDs for the objects (e.g., player 1, player 2, ball) are maintained throughout the frames.

2. Motion Data Storage: The tracker updates and stores the movement paths, allowing the system to generate insights like distance covered, speed, and direction of movement for each object.

D. Team Assignment with K-Means Clustering

1. Segmentation: To classify players into teams, K-Means clustering is used. The algorithm clusters players based on their uniform colors, which are extracted from the detected objects in each frame.

- Step 1: Extract the pixel regions corresponding to the players in each frame.
- Step 2: Convert the image region to the HSV (Hue, Saturation, Value) color space, as it provides better clustering performance than the RGB color space.
- Step 3: Apply the K-Means algorithm to group players into clusters based on the predominant color in the uniform (e.g., blue for Team A, red for Team B).

2. Output: The clustering algorithm assigns each player to a team, which helps in understanding the formations, team behavior, and interactions on the field.

E. Ball Tracking using Optical Flow

1. Optical Flow Algorithm: Optical flow is used to track the movement of the ball, providing real-time insights into possession and ball trajectories.

- Step 1: Convert consecutive frames into grayscale.

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- Step 2: Apply the Farneback or Lucas-Kanade optical flow algorithm to detect the motion between consecutive frames.
- Step 3: Track the ball's position and calculate its velocity and acceleration in each frame.

2. Ball Possession Metrics: The system tracks ball possession, which is crucial for analyzing team strategies. The percentage of possession by each team is calculated by measuring the amount of time each team controls the ball.

F. Movement Analysis and Metrics Calculation

1. Movement Analysis: The movement of players is analyzed using the output of object tracking and optical flow. Metrics such as speed, distance covered, and direction of movement are calculated.

- Step 1: The system computes the distance between a player's position in consecutive frames.
- Step 2: Speed is calculated by dividing the distance by the time elapsed between frames.
- Step 3: Movement direction and player orientation are also tracked, providing insights into the player's strategic positioning.

2. Tactical Insights: Movement data allows for the analysis of individual and team tactics. For example, coaches can evaluate how well players maintain defensive or offensive positions, and how the team transitions between different phases of play.

G. Perspective Transformation

1. Coordinate Transformation: The system uses perspective transformation to adjust the detected object coordinates to real-world units (such as meters), compensating for the depth and perspective distortion in the video feed.

- Step 1: Four reference points on the football field are selected (e.g., the four corners of the pitch).
- Step 2: A transformation matrix is computed to correct the field's perspective.
- Step 3: The object coordinates are transformed to real-world units, ensuring accuracy in speed and distance calculations.

H. Result Visualization and Reporting

1. Data Visualization: The system outputs the analysis results in user-friendly dashboards or video overlays. These visualizations include metrics like speed, distance covered, ball possession percentage, and heatmaps showing player movements.

- Step 1: The results are visualized in interactive dashboards, where users can explore the performance of individual players and teams.
- Step 2: Video overlays show the movement of players and the ball with annotations for quick reference during post-match analysis.

2. Report Generation: A detailed report is generated, summarizing key insights from the match, including performance metrics, tactical observations, and player comparisons. This report is saved for further review by coaches or analysts.

3. System Evaluation

The system is evaluated based on several criteria, such as:

- Accuracy: The ability of the system to detect and track objects with high precision.
- Real-time Performance: The system's ability to process video frames and generate outputs in real-time.
- Scalability: The system's ability to handle multiple video sources and large datasets from various match scenarios.
- Usability: The ease with which users (coaches, analysts, etc.) can interpret and act on the results provided by the system.

The evaluation is conducted using test datasets from different football matches, including both professional and amateur games. Performance metrics like detection accuracy, tracking stability, and real-time processing speed are measured and compared to traditional analysis systems.

4. Conclusion

The implementation of the football analysis system provides a comprehensive, real-time, and cost-effective solution for analyzing football matches. By integrating advanced machine learning models like YOLOv8, K-Means clustering, optical flow, and perspective transformation, the system offers detailed insights into player performance, team

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dynamics, and match strategies. This automated system simplifies the analysis process, making it accessible for teams at all levels, from professional clubs to amateur teams, while providing accurate and actionable data for coaches, analysts, and fans.

VI. RESULTS

YOLOv8 processes each video frame to detect key objects on the football field, such as players, referees, and the ball. The output includes bounding boxes around each detected object, providing their exact positions within the frame. Each object is also assigned a class label, distinguishing players from referees or the ball. For instance, the system can identify a group of players in action and accurately locate the ball's position, ensuring no critical game event is missed.The model associates a confidence score with every detection, indicating the reliability of its classification. For example, a confidence score of 0.98 for a detected player suggests high certainty in the prediction. YOLOv8's ability to process frames in real time ensures continuous tracking of fast-paced movements, such as a player's sprint or the ball's trajectory after a kick. This dynamic capability is crucial for analyzing game sequences as they unfold.

The output can also include unique object IDs, enabling the system to track specific players or referees across multiple frames. This tracking feature helps analyze individual performances, such as a player's movement patterns or distance covered during the game. Additionally, YOLOv8's detailed annotations provide the groundwork for advanced analyses, such as identifying team formations or player interactions, offering invaluable insights for coaches, analysts, and fans.

Figure 3 Output Video of the System.

Visual Representation: The major output of this image is a visual representation of the football field on a real-time basis during a live match. All the players on the field are represented, color-coded for easy identification of the teams. Players may be shown as rectangles with each rectangle having details such as speed and distance covered.

Real-time Data Overlay: The visualization is more than an image; it takes in real-time data overlays, meaning the position of the players and statistics are being updated dynamically during the match. This will provide a dynamic and interactive view of the game for real-time monitoring of player movement and strategies of both the teams.The most likely key performance indicators in the image are ball possession percentage for each team. The information combined with the graphical illustration of the players' positions would be helpful in determining the flow of the game and the likelihood of winning for each team. Such analysis is essential for coaches and analysts to make decisions during and after the match. Essentially, the output format of this image provides a detailed and dynamic view of the football match, where the visual representation is combined with real-time data analysis to present actionable insights to the game's participants.

VII. CONCLUSION

The advanced football analysis system is based on superior machine learning, computer vision, and deep learning technology to provide detailed and accurate insights into the game. Using YOLOv8 for object detection, this system provides very high accuracy in identifying players, referees, and footballs, where custom training helps tailor it towards specific needs. K-Means clustering effectively segments the players based on the t-shirt colors, so precise team assignments are made; optical flow measurements and perspective transformations enable accurate tracking of movement and distance calculations. Through rigorous testing, the system's reliability has been validated-including its ability to handle edge cases and maintain computational efficiency-with user feedback that stresses its practical utility in real-world scenarios. New object detection models, real-time optimization, and adaptive clustering techniques may further enhance the accuracy and responsiveness of future capabilities. The inclusion of advanced optical flow methods, depth sensors, and dynamic 3D modeling will refine movement tracking and scene depth representation, and further metrics will include acceleration and exertion levels, offering a deeper view into performance. Moreover, extension of the system to make it handle larger datasets while integrating it with other related sports analytics tools will improve on its versatility and applicability across games.

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