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Soccer Performance Analytics: Leveraging YOLOv11 and Image Processing for Data-Driven Insights

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ABSTRACT

In the rapidly evolving field of soccer analytics, leveraging advanced technologies is essential for performance evaluation and strategic decision-making. This project utilizes the newly introduced YOLOv11, a state-of-the-art object detection model, to detect and track players and the ball in video footage from multiple camera angles. Integrated object trackers ensure continuity across frames, while K-means clustering classifies players into teams based on t-shirt colors. Through image processing techniques like optical flow and perspective transformation, player movements are converted into real-world measurements, enabling precise assessments of speed and distance covered. Additionally, Gemini AI is incorporated to automatically generate detailed reports based on the analyzed data, providing comprehensive insights for coaches, analysts, and sports authorities. This system aims to empower data-driven decision-making in soccer management and elevate the effectiveness of performance analysis.

Keywords: *Soccer Analytics, YOLOv11, Object detection, Player Tracking, Ball Detection, Machine Learning, K-means clustering, Optical flow, AI reporting, Image Processing, Perspective Transformation.*

1. INTRODUCTION

The field of soccer analytics has seen a major shift in recent years, thanks to the integration of advanced technology and data-driven methods. As soccer's popularity grows worldwide, there is an increasing need for innovative tools to assess player performance, develop strategies, and make informed decisions. With the huge amount of data generated during matches, teams and coaches face the challenge of processing and analyzing this information to gain insights that can have a significant impact on performance.

A key advancement in this area is the use of computer vision techniques, which apply algorithms to analyze visual data from video feeds. This technology allows for the real-time detection and tracking of players and the ball, offering valuable insights into different aspects of gameplay. By using sophisticated models like YOLOv11, teams can accurately identify player movements and track ball acquisition, providing important data about possession and interactions between players. This enables coaches and analysts to better understand player dynamics, including speed, distance covered, and positioning during the match.

Tracking ball acquisition is especially important in soccer analytics. Knowing which players are effective at gaining possession and how they interact with others helps coaches make more informed decisions about formations and strategies. For example, analyzing possession data can show which players are suited for specific roles, such as defenders or forwards.

This detailed information allows teams to improve training and individual player performance, which contributes to the overall success of the team.

In addition, machine learning has introduced predictive models that go beyond traditional performance analysis. These models use past match data to forecast future performance, evaluate injury risks, and assess overall team dynamics. By examining trends in historical data and considering factors like player statistics and environmental conditions, predictive models provide useful insights that can improve decision-making in soccer management.

For instance, machine learning algorithms can evaluate a player's past performance to predict how they might perform in an upcoming match. By taking into account factors such as fatigue and past performances against certain teams, teams can make data-driven decisions about player selection and tactics. This predictive ability not only improves a team's chances of winning but also helps prevent injuries by identifying players who need rest or recovery.

Another advantage of these technologies is their potential to improve training. With real-time data on player performance and ball acquisition, coaches can customize training sessions to target specific weaknesses or build on strengths. For instance, if data shows that a player struggles with ball control under pressure, specific drills can be designed to help them improve in that area. This approach to training helps maximize player development and team performance.

This study examines how these advanced techniques in soccer analytics can help coaches, players, and sports organizations. By using a combination of computer vision, ball acquisition tracking, and machine learning, teams can optimize training, refine strategies, and improve overall performance. As more teams adopt these data-driven approaches, the ability to make better decisions in soccer management grows.

Moreover, soccer analytics provides deeper insights into the game, helping coaches adjust to changing match conditions. By analyzing data in real-time, teams can quickly adapt their tactics to match the unfolding game, ensuring they stay competitive. This flexibility is crucial in high-pressure situations where the outcome can depend on a coach’s ability to quickly interpret the game and respond.

In conclusion, the use of advanced technology in soccer analytics marks a major shift in how teams approach the sport. By combining computer vision, ball acquisition tracking, and machine learning, coaches and analysts can gain valuable insights that enhance player performance, guide strategic decisions, and contribute to team success. As soccer continues to evolve, data-driven methods will play an increasingly important role in shaping the future of the sport.

2. LITERATURE SURVEY

[1] In their study, Gabriel Fialho et al. explore various AI techniques for forecasting outcomes in sports, particularly soccer and basketball. Analyzing over 200,000 soccer matches, the researchers found that Bayesian Networks delivered an impressive prediction accuracy of 92%, while Artificial Neural Networks (ANN) achieved an 85% accuracy rate. These findings indicate the potential of AI in sports analytics. However, the study also points out significant challenges, such as the scarcity of publicly available data and the risk of overfitting, especially when working with smaller datasets. The tendency for these models to struggle in predicting draws highlights the complexities involved in accurately forecasting sports outcomes.

[2] Haixia Zhao and colleagues present a sophisticated neural network-based model that leverages error backpropagation and genetic algorithms to predict athletic performance. This model boasts a remarkable prediction accuracy of 97.6%, significantly outperforming traditional prediction methods. However, the complexity of the neural network necessitates substantial computational resources, which may not be readily available in all contexts. The study emphasizes that the model's effectiveness is heavily dependent on the quality of input data, with a maximum error margin of 36.12% underscoring inconsistencies in performance predictions across different sports and athlete profiles. This highlights the ongoing challenge of generalizing findings in sports analytics.

[3] In their research, Shitanshu Kusmakar et al. utilize event stream data to explore player interactions within soccer games, aiming to predict outcomes like goal attempts and match winners. The model achieved prediction accuracies of 75.2% for segmental outcomes and 66.6% for overall match winners, validated on larger datasets. These results suggest the potential of machine learning in enhancing soccer analytics. However, the study cautions that performance can vary based on the complexity of individual matches and the quality of the data used. Additionally, a narrow focus on shot events could overlook broader match dynamics, indicating a need for more comprehensive analysis frameworks in sports prediction.

[4] Wei-Jen Chen et al. present a hybrid prediction model for NBA game outcomes by integrating several data mining techniques, including Extreme Learning Machines (ELM), MARS, K-Nearest Neighbors (KNN), XGBoost, and Stochastic Gradient Boosting (SGB). The two-stage XGBoost model emerged as the top performer, demonstrating superior prediction accuracy. However, the model's heavy reliance on game-lag information may limit its applicability to other sports or leagues. The study also notes that as datasets grow larger, computational complexity increases, potentially making real-time application more challenging. These findings highlight both the strengths and limitations of current methodologies in sports outcome predictions, emphasizing the need for adaptable models across different contexts.

[5] Shaoliang Zhang et al. develop a predictive model using lasso-logistic regression to assess factors influencing soccer match outcomes, specifically in the UEFA Champions League. Their research identifies key elements, such as counterattacks and shots on target, which positively affect match results, while factors like crosses and yellow cards can have a detrimental impact. The model demonstrates high accuracy and calibration, but it relies heavily on historical data, which may not reflect real-time dynamics of live matches. Additionally, the complexity of the nomogram necessitates expert interpretation for practical application, indicating a need for user-friendly interfaces that can bridge the gap between complex data analysis and actionable insights for coaches and analysts.

[6] In their extensive review, Banoth Thulasya Naik et al. examine the applications of computer vision techniques in sports video analysis. The authors discuss critical applications such as player detection and tracking, emphasizing the advancements made possible by AI and GPU-based systems. However, they also highlight significant challenges, including the lack of comprehensive public datasets and difficulties in tracking players due to occlusion and rapid movements. Furthermore, the necessity for optimization in real-time analysis poses additional hurdles for practical implementations. This review calls for more accessible datasets and improved methodologies to enhance the accuracy and efficiency of computer vision applications in the sports industry.

[7] Keerthana Rangasamy and colleagues conduct a comparative review of traditional approaches versus deep learning methods for analyzing complex human movements in sports videos. Their findings suggest that deep learning techniques generally outperform traditional methods, especially in recognizing intricate patterns and movements. However, the study notes that deep learning models require large datasets and substantial computational power, which can pose challenges for real-time applications. In scenarios where data is limited or tasks are simpler, traditional methods may still hold advantages. The authors suggest that a hybrid approach, combining both deep learning and traditional techniques, could effectively address varying complexities in sports video analysis.

[8] Zhiqiang Pu et al. present a systematic review focusing on the integration of soccer analytics and artificial intelligence through the OODA (Observe, Orient, Decide, Act) loop framework. The study investigates both real-world and simulated environments to enhance decision-making models powered by deep reinforcement learning. The review reveals that while AI significantly improves insights into tactical decisions and player evaluations, challenges such as limited access to real-world data and the complexity of AI models hinder broader application. Additionally, the integration of AI into live match scenarios presents logistical difficulties. This review emphasizes the need for ongoing research to overcome these challenges and fully realize the potential of AI in soccer analytics.

[9] In their research, Banoth Thulasya Naik and Mohammad Farukh Hashmi propose an improved YOLOv3-based model for real-time detection and tracking of players and the ball in soccer videos. The model enhances detection accuracy significantly and employs the SORT algorithm for effective tracking. This system supports real-time analysis, providing coaches with valuable insights into player performance and game dynamics. However, the model faces challenges, particularly its heavy reliance on extensive self-annotated training data and potential issues with detection accuracy in low-quality video feeds. Furthermore, the ability to generalize findings to other sports remains a concern, indicating a need for adaptable models across different contexts in sports analytics.

[10] Yifei Zheng and Hongling Zhang develop the YOLO-OSA network, a lightweight object detection model designed to enhance sports video analysis. By integrating the YOLO framework with DenseNet, their findings indicate that higher resolution images significantly improve detection accuracy, achieving a precision of 21.70% and recall of 54.90%. Although the lightweight architecture allows for faster analysis, limitations in precision and recall highlight the need for further refinement. Additionally, the model's dependency on high-resolution footage suggests that practical implementation may be challenging without advanced technical expertise. The study underscores the potential for lightweight models in sports video analysis while pointing out the necessity for ongoing optimization to enhance performance in real-world scenarios.

3. SUMMARY OF LITERATURE SURVEY

In conclusion, the reviewed papers highlight the significant advancements in artificial intelligence and machine learning within sports analytics, particularly in soccer and basketball. Each study presents unique methodologies and applications, collectively underscoring the potential of AI to enhance prediction accuracy and performance analysis. However, challenges remain, including data availability, model generalization, and the complexities of real-time integration. The findings suggest promising approaches, such as hybrid models, deep learning techniques, and advanced computer vision applications, which pave the way for more effective and insightful sports analytics. As the field continues to evolve, ongoing research and innovation will be essential in overcoming existing barriers and fully harnessing AI's capabilities in sports analysis.

4. METHODOLOGY

This methodology provides a refined, multi-phased approach to soccer game analysis by integrating the powerful YOLOv11 object detection model with advanced machine learning, computer vision, and deep learning techniques. Each phase of analysis is meticulously designed to capture, process, and analyze game data to extract actionable insights into player and team performance, enabling data-driven decision-making for coaches, analysts, and sports managers.

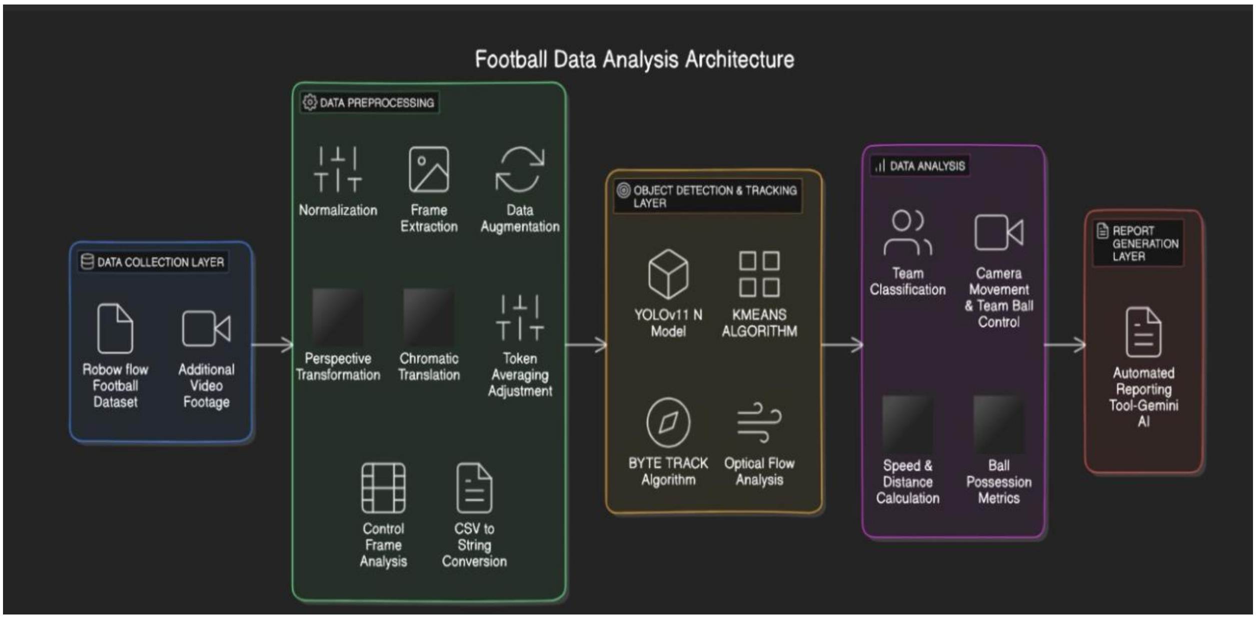

Fig. 1 Architecture of Football Data Analysis

Data Collection

This foundational phase focuses on gathering high-quality, annotated video footage and additional resources to support precise analysis.

- *Primary Dataset:* The Roboflow Football Dataset from Kaggle is chosen for its high-resolution video quality and comprehensive annotations. The dataset provides essential positional information on players, the ball, referees, and other game elements.
- *Annotation Details:* Annotations include real-time data on player positions, ball trajectories, and critical events, which are essential for tracking, segmentation, and feature extraction.
- *Supplementary Data:* Additional video footage from multiple camera angles and perspectives is incorporated to enhance depth, accuracy, and detail, enabling multidimensional insights into player and ball dynamics.

Data Preprocessing

Preprocessing transforms raw video footage into a structured, standardized format, preparing it for efficient and accurate analysis.

- *Frame Extraction:* Each video is decomposed into individual frames, allowing for granular, frame-by-frame analysis. This approach enables the accurate capture of player movements, ball interactions, and tactical changes throughout the match.
- *Normalization:* Pixel values are normalized to a consistent range [0, 1], which optimizes the model's training efficiency and stability by ensuring uniformity across all images.
- *Data Augmentation:* Techniques such as rotation, flipping, and scaling are applied to generate diverse examples that simulate in-game variations, creating a more robust model by reducing overfitting and enhancing generalization.
- *Perspective Transformation:* OpenCV's perspective transformation corrects for depth and distortion in each frame. By translating pixels into real-world measurements (meters instead of pixels), this technique provides accurate metrics for player speed, distance, and positioning, ensuring realistic performance assessment.

Object Detection and Tracking

In this phase, Ultralytics YOLOv11 is used to identify and track critical game elements, offering high-speed, precise object detection.

- *Ultralytics YOLOv11 Detection:* Ultralytics YOLOv11, a cutting-edge object detection model, is selected for its ability to deliver real-time, highly accurate detections. Its unique architecture optimizes the detection of small and fast-moving objects such as the soccer ball, players, and referees in each frame, ensuring no critical detail is missed.

- *Bounding Box Segmentation:* YOLOv11's bounding boxes are tailored to segment players, enabling focused analysis of t-shirt colors for team classification. By isolating the t-shirt region, the model accurately segments players by jersey color, simplifying team classification for subsequent analysis.
- *Object Tracking with Byte Track:* Byte Track, a powerful tracking algorithm from the Supervision library, is employed to ensure the continuity of tracked objects, such as players and the ball, across frames. This tracking approach maintains unique and consistent IDs for each object, enabling precise movement trajectories that reflect player actions and interactions throughout the game. By establishing reliable, frame-to-frame object association, Byte Track facilitates detailed time-series analysis, offering insights into player positioning, team formations, and ball movement. Its robust tracking capabilities support the identification of key events and game dynamics with high accuracy, even under challenging conditions, such as rapid motion or crowded scenes..
- *Camera Motion Compensation with Optical Flow:* Optical flow analysis measures camera movement across frames, distinguishing between player motion and camera shifts. This ensures that measurements of player speed, distance, and positioning accurately reflect true motion, regardless of camera movement or angle changes.

Data Analysis

The data collected from detection and tracking is analyzed to produce actionable insights into player and team performance.

- *Team Classification with K-means Clustering:* Using segmented t-shirt color regions from YOLOv11's bounding boxes, K-means clustering automatically classifies players into teams based on jersey colors. This team-based segmentation allows for streamlined and accurate analysis of team dynamics and interactions during gameplay.
- *Movement and Speed Analysis with Perspective Transformation:* Perspective transformation adjusts for camera distortion, providing real-world metrics for speed and distance covered. By converting pixel-based measurements into meters, this approach offers a precise calculation of player exertion, stamina, and spatial awareness on the field.
- *Speed and Distance Calculation:* Using continuous tracking data, player speed and distance covered are calculated accurately. These metrics are essential for assessing physical performance, endurance, and movement efficiency, giving coaches insights into individual player capabilities and overall team cohesion.
- *Ball Possession and Acquisition Metrics:* Metrics for ball possession and acquisition are calculated to assess each player's influence on game flow and control. These metrics provide tactical insights into a player's effectiveness in acquiring and maintaining possession, helping to identify playmakers and critical contributors to team strategy.

Advanced-Preprocessing Techniques

Preprocessing transforms raw video footage into a structured, standardized format, preparing it for efficient and accurate analysis.

- *Chromatic Translation:* This technique converts RGB color values into descriptive color names, enhancing the identification of player jerseys and other color-coded elements in the footage. This step aids in team classification and improves visual clarity.
- *Token Averaging Adjustment:* This process involves averaging the initial and moved positions of tracked objects (players and the ball), which helps in refining the positional data and minimizing discrepancies caused by rapid movements. It also allows for a reduction in the number of tokens used in the analysis.
- *Control Frame Analysis:* This method examines the frames in which specific players control the ball, providing insights into possession dynamics and player interactions. It focuses on identifying the most relevant frames to capture critical moments of play.
- *CSV to String Conversion:* This involves transforming structured CSV data into a string format for easier processing and manipulation. This conversion is essential for integrating various datasets and making the data more accessible for analysis.

Advanced-Preprocessing Techniques

- *Gemini AI-Driven Reporting System:* The Gemini AI reporting system generates comprehensive, automated reports that summarize and visualize key insights for easy consumption. This automated reporting tool compiles analyzed data into a structured report, highlighting key performance indicators (KPIs) such as player movement metrics, goals taken, and predictive performance statistics.

5. RESULTS AND DISCUSSION

The soccer analysis utilizing YOLOv11 and advanced image processing techniques aims to uncover critical insights into player performance and team dynamics.

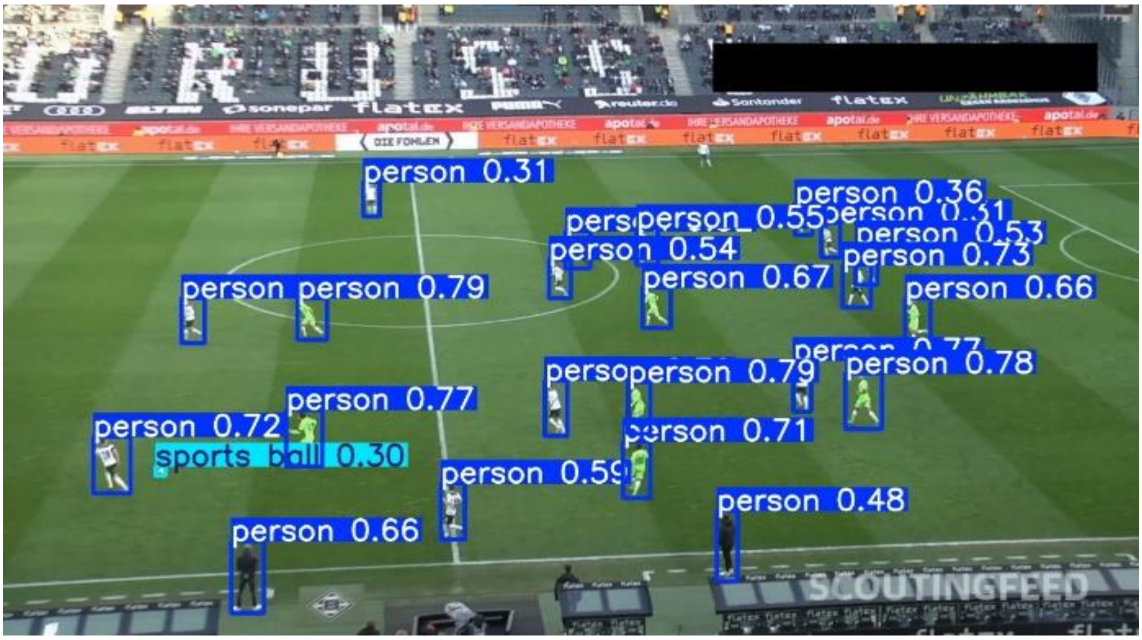

Fig. 2 Object Detection using Pre-Trained YOLOv11

In Figure 2, the YOLO v11 model, trained at a baseline level without additional image processing, is applied to detect objects within the frame. This preliminary model can identify only generic objects like "person" and "sports ball." However, it exhibits limitations in accurately detecting the ball, leading to inconsistent and unreliable tracking.

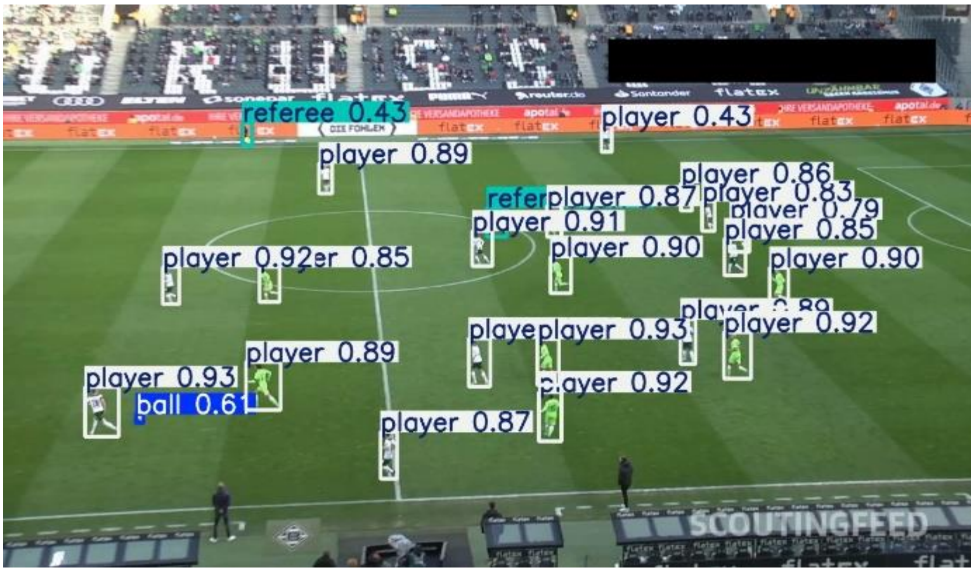

Fig. 3 Object Detection using Custom Trained YOLOv11

In Figure 3, the YOLO v11 model is enhanced with the Robowflow dataset, improving its capacity to recognize specific entities within each frame. It can now differentiate between players, referees, goalkeepers, and the ball, providing more precise annotations and facilitating better detection.

Building on this, our project applies advanced image processing techniques to further enhance YOLO v11's functionality. This refined model offers comprehensive capabilities, including unique player tagging, precise tracking of player speed and distance, team differentiation, efficient ball tracking with player-to-player movement, compensation for camera shifts, and team ball control analysis. These improvements deliver a robust, real-time solution for in-depth sports analysis.

The analysis of soccer performance from the input video, comprising 749 frames, yielded valuable insights through the application of the Ultralytics YOLOv11 model and advanced tracking techniques. The use of bounding box segmentation facilitated effective team classification based on jersey colors, deepening the examination of team dynamics. In frame 0, several players were detected with specific coordinates detailing their positions:

Player 1:

Coordinates: [1276.39, 393.95, 1306.12, 463.70]

Team Color: [144.16, 227.51, 180.43]

Player 2:

Coordinates: [586.66, 588.98, 631.10, 674.03]

Team Color: [228.83, 229.03, 219.14]

This level of detail allowed for precise tracking of player movements and interactions throughout the match. The utilization of Byte Track ensured continuous identification of players across frames, which was critical for analyzing their movement patterns and contributions to gameplay. Additionally, the camera's shifting position from frame to frame, as illustrated in Figure 5, significantly influenced the measurement of player actions. Optical flow analysis played a vital role in distinguishing player movements from camera shifts, ensuring accurate capture of metrics such as speed and distance.

The methodology not only unveiled essential performance indicators—like player speed and distance travelled—but also provided insights into ball possession and acquisition metrics. This comprehensive analysis equips coaches and analysts with actionable data, enhancing their capacity to make informed, data-driven decisions in soccer management.

The compiled player tracking and ball control data were exported to CSV files, facilitating further analysis and detailed reporting. This systematic organization of relevant metrics—such as player positions, speeds, distances, and team assignments—ensures accessibility and insight extraction. Subsequently, a comprehensive match report was generated using Google's Gemini AI model. This report synthesizes the collected tracking data into a narrative format, highlighting key performance indicators, overall game dynamics. The integration of analytics into the report enriches the context for understanding player behaviors and team strategies. Finally, the generated report was saved as a text file, preserving the insights for easy sharing among analysts, and stakeholders in soccer management. This process enhances the decision-making framework, enabling data-driven strategies for future matches and training sessions.

Fig. 4 Enhanced Object Detection and Tracking

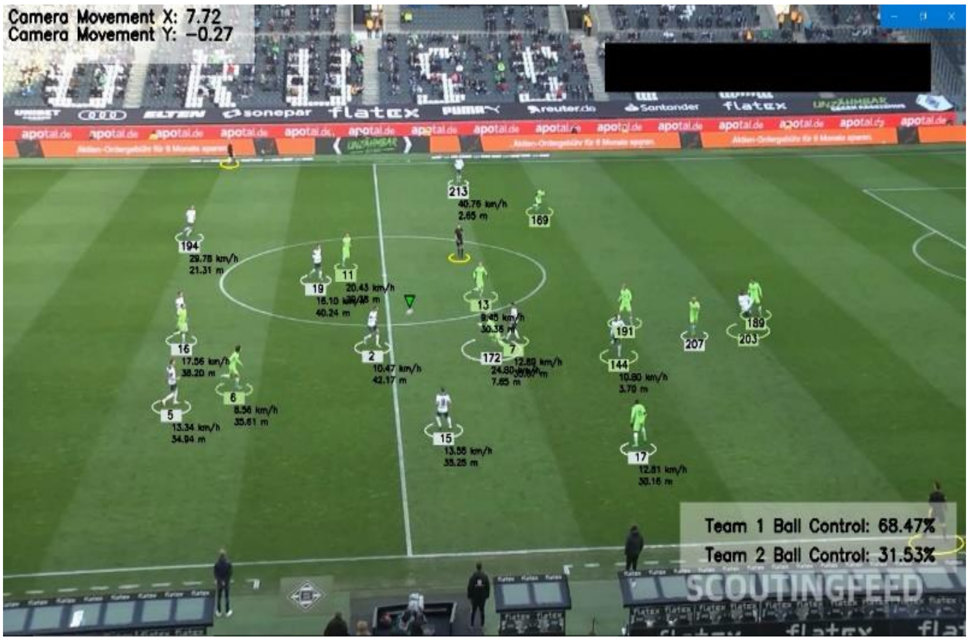

Fig. 5 Enhanced Object Detection and Tracking

6. FUTURE SCOPE

Building upon the methodology established for soccer analytics using the Robowflow Football Dataset, several avenues for future work are identified to enhance the depth and applicability of the research.

- *Implementation of the has_ball Parameter:* Future work will focus on integrating the has_ball parameter to analyze individual player possession, allowing for detailed tracking of ball movement between players instead of just team dynamics. This enhancement aims to provide deeper insights into player contributions and playmaking strategies.
- *Enhanced Object Detection and Tracking:* Future iterations could refine the YOLOv11 model with additional datasets from various soccer leagues. This would improve the model's adaptability to different playing styles. Implementing advanced tracking algorithms, such as deep learning-based multi-object tracking (MOT), could enhance the accuracy of player and ball tracking, especially during complex plays. Additionally, training alternative models like YOLOv9 and YOLOv5 and comparing their performance against YOLOv11 could provide insights into model efficiency and accuracy in soccer analytics.
- *User-Centric Applications:* Creating an interactive dashboard to visualize key metrics in real-time would empower coaches to make data-driven decisions during matches. Developing a mobile application could further facilitate access to performance analytics on-the-go, making soccer analytics more accessible to grassroots coaches.

7. CONCLUSION

The integration of advanced technologies in soccer analytics, particularly through the use of YOLOv11 for real-time player and ball detection, marks a significant advancement in performance evaluation and strategic decision-making. This study highlights how object tracking and K-means clustering can effectively analyze player movements, while techniques like optical flow and perspective transformation provide accurate real-world metrics for speed and distance. The Gemini AI-driven reporting system further streamlines the communication of findings, making it easier for analysts to access critical performance metrics of each player and adapt strategies in real-time.

Ultimately, this research combines computer vision, AI, player tracking, and image processing to empower coaches and analysts with insights that can significantly improve team performance. The findings pave the way for data-driven decision-making in soccer management, offering a promising outlook for future advancements in the sport.

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