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Video Processing and Data Analysis for Football Matches using Deep Learning

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Abstract:

Football analytics has become an indispensable component of modern sports performance evaluation, driven by the increasing availability of match video data and advancements in computer vision and deep learning technologies. Traditional football analysis techniques rely heavily on manual video inspection and subjective judgment, which limits scalability and introduces human bias. To overcome these limitations, this paper presents a comprehensive automated football analytics framework capable of extracting tactical and physical insights directly from broadcast match videos. The proposed system integrates deep learning-based object detection, multi-object player tracking, team identification using colour-based clustering, and holography-based field projection to enable metric analysis. Using this unified pipeline, the system computes detailed performance indicators such as player speed, total distance covered, heatmaps, positional distribution, and basic tactical structures. The framework is designed to operate efficiently under real-world match conditions, including dynamic camera motion, occlusions, and varying illumination. Experimental evaluation on multiple broadcast football matches demonstrates that the proposed approach achieves reliable detection accuracy, stable tracking performance, and near real-time processing capability. The results indicate that the system is suitable for post-match analysis, coaching support, scouting, and broadcast enhancement applications.

Keywords — **Football Analytics, Deep Learning, Computer Vision, Player Tracking, Tactical Analysis.**

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I. INTRODUCTION

Football has evolved into one of the most analytically driven sports in the modern era, where data-informed decision-making plays a vital role in tactical planning, player development, performance evaluation, and injury prevention. With the exponential growth in the availability of broadcast and training footage, video analysis has become a central tool for clubs, analysts, coaches, and broadcasters. Every professional football match generates hours of visual data that capture player movement, team structure, ball dynamics, and tactical patterns. Extracting useful information from this data, however, remains a com plex and resource-intensive task. Traditional football analysis methods rely heavily on manual observation, annotation, and subjective interpretation by analysts. While expert analysis can provide valuable insights, manual approaches are time-consuming, inconsistent, and difficult to scale across multiple matches or competitions. Moreover, human-based analysis is prone to bias and fatigue, which limits its reliability when dealing with large datasets or real-time scenarios. These limitations have motivated the adoption of automated and semi-automated analysis techniques that leverage advances in computer vision and machine learning. Recent progress in deep learning has significantly transformed video understanding tasks, including object detection, tracking, segmentation, and action recognition. Convolutional neural networks and more recent transformer-based architectures have demonstrated exceptional performance in extracting high-level semantic information from visual data. In the context of football analytics, these techniques enable automated identification of players, referees, and the ball, tracking of player trajectories over time, and extraction of spatial-temporal features that are essential for tactical analysis. Despite these advancements, automated football video analysis remains a challenging problem. Broadcast footage typically involves dynamic cam era motion, including panning, tilting, and zooming, which introduces instability in visual tracking. Frequent occlusions occur during crowded situations such as corner kicks, free kicks, and defensive blocks. Lighting conditions vary significantly across stadiums, weather conditions, and match timings, affecting colour consistency and visibility. Additionally, the football itself occupies a very small region in the frame, making reliable detection difficult under fast motion and motion blur. Another critical challenge in football analytics is the need to translate pixel-level information into meaningful physical and tactical metrics. Raw detections in image coordinates are insufficient for performance evaluation unless they can be mapped to real world pitch coordinates. Accurate measurement of player speed, distance covered, positional heatmaps, and team compactness requires a reliable transformation between the camera view and the football field geometry. Without such mapping, derived metrics lack physical interpretability and cannot be compared across matches. Furthermore, meaningful tactical understanding requires more than isolated detections or tracks. It demands long-term temporal consistency, accurate team identification, and structured analysis of spatial relationships between players. Concepts such as formation shape, defensive compactness, pressing intensity, and zonal occupation emerge only when player trajectories are analysed over extended periods. Automated systems must therefore integrate detection, tracking, team classification, and spatial modelling into a unified pipeline. In recent years, several research efforts have explored automated sports analytics using computer vision and machine learning techniques. While many approaches focus on individual components such as player detection or tracking, fewer systems provide a complete end-to-end solution capable of generating actionable tactical insights from raw broadcast video. Moreover, many existing systems are designed for controlled environments or multi-camera setups, limiting their applicability to standard broadcast footage commonly available to analysts and broadcasters. This paper addresses these challenges by presenting a comprehensive football analytics framework that operates directly on single-view broad cast video. The proposed system integrates deep learning-based object detection, multi-object tracking, team identification through colour-based clustering, and homograph-based field projection within a unified architecture. By combining these components, the system enables robust extraction of player trajectories and computation of both physical and tactical performance metrics. The primary objective of this work is to design an automated analytics pipeline that is accurate, scalable, and capable of near real-time operation under realistic match conditions. The system is intended to support a wide range of applications, including post match tactical analysis, player performance evaluation, scouting, and broadcast enhancement. Em phasis is placed on modularity, allowing individual components to be improved or replaced as new techniques emerge. The remainder of this paper is organized as follows. Section II describes the materials and methods used in the proposed system, including data preparation, detection, tracking, team identification, and field projection. Section III presents the experimental results and discusses the performance of the system across different analytical dimensions. Section IV concludes the paper by summarizing the main findings and outlining potential directions for future work.

II. MATERIALS AND METH ODS

This section describes in detail the materials, datasets, preprocessing steps, and computational methods employed in the proposed football analytics framework. The methodology is designed to ensure reproducibility and robustness under real-world broadcast conditions.

A. Dataset Description and Video Acquisition

The experimental evaluation is conducted using broadcast football match videos obtained from publicly available sources. The dataset consists of full match recordings and extended highlights captured under diverse stadium environments, including day and night matches, varying weather conditions, and different camera configurations. Videos are provided in standard MP4 format with frame rates ranging between 25 and 30 frames per second and resolutions up to 1920 × 1080 pixels. The dataset includes frequent camera operations such as panning, tilting, and zooming, which closely resemble professional broadcast scenarios. Such conditions introduce significant challenges for auto mated analysis and provide a realistic benchmark for evaluating system performance. No manual annotations are used during inference, enabling fully auto mated analysis.

B. Frame Extraction and Preprocessing

Each input video is decomposed into individual frames prior to analysis. To ensure compatibility with the detection network, frames are resized to a fixed resolution while preserving aspect ratio. Frame normalization is applied to reduce the impact of illumination variations caused by stadium lighting, shadows, and weather conditions. Camera motion often introduces jitter that adversely affects tracking accuracy. To mitigate this effect, feature-based stabilization is applied by detecting salient key points across consecutive frames and estimating a transformation that minimizes frame-to frame displacement. Additionally, contrast enhancement techniques are employed to improve the visibility of distant players and the football, particularly in wide-angle shots.

C. *Object Detection Module*

Player and ball detection is performed using a deep learning-based object detection model trained to identify key entities present in football matches, including players, referees, and the ball. The detector processes each frame independently and outputs bounding boxes, class labels, and confidence scores. The detection model is optimized to achieve a balance between accuracy and inference speed, enabling near real-time processing. Special emphasis is placed on detecting small objects such as the football, which often appears blurred or partially occluded during 3 high-speed plays. The model's robustness allows it to handle variations in camera angle, scale, and player appearance.

D. Multi-Object Player Tracking

To maintain consistent player identities across frames, a multi-object tracking algorithm is employed. The tracker uses motion prediction to estimate the future position of each player based on historical observations. Detected bounding boxes are associated with existing tracks using spatial proximity and temporal consistency measures. This tracking strategy enables smooth trajectory estimation and reduces identity switches during short-term occlusions. Tracks are initialized when new players enter the scene and terminated when players exit the camera view for an extended duration. The resulting trajectories form the basis for sub sequent physical and tactical analysis.

E. Team Identification Using Colour-Based Clustering

Accurate team identification is essential for tactical interpretation. The proposed system identifies team affiliation by analysing jersey colour information. For each detected player, a torso region is extracted from the bounding box to minimize background interference. The extracted region is converted from RGB to HSV colour space, which provides improved robust ness to lighting variations. Colour histograms are computed and clustered using an unsupervised clustering algorithm to separate players into two distinct teams. Temporal smoothing is applied to stabilize team labels across consecutive frames and prevent frequent reassignment.

F. Homograph-Based Field Projection

To enable metric analysis, detected player positions in image coordinates are mapped to real-world pitch coordinates using homograph transformation. Key field markings such as boundary lines, centre circle, and penalty box edges are used to estimate the trans formation matrix. Once projected, player trajectories are represented in a common pitch coordinate system. This map ping allows accurate computation of physical metrics such as speed and distance covered and enables spatial analysis including heatmap generation and zonal occupancy estimation.

G. Physical Performance Metric Computation

Using projected trajectories, the system computes multiple physical performance metrics for each player. Instantaneous speed is estimated by measuring frame-to-frame displacement in pitch coordinates, while total distance covered is obtained by ac cumulating displacement over time. Acceleration and deceleration patterns are analysed to identify high-intensity actions such as sprints. These metrics provide objective indicators of player workload and physical contribution during different phases of the match.

H. Tactical Metric Extraction

Beyond physical performance, the system extracts tactical metrics that describe team behaviour and structure. Positional heatmaps are generated using kernel density estimation to visualize spatial occupancy over time. Zonal analysis divides the pitch into predefined regions and measures player presence in each zone. Team-level metrics such as centroid movement and average inter-player distance are computed to analyse formation compactness and structural stability. These metrics provide insight into pressing behaviour, defensive organization, and attacking shape.

I. System Implementation Details

The proposed framework is implemented using Python and widely adopted computer vision and deep learning libraries. GPU acceleration is utilized to enable efficient processing of high-resolution video 4 streams. The modular architecture allows individual components such as detection or tracking to be updated independently without affecting the overall pipeline.

J. Experimental Setup

All experiments are conducted on a workstation equipped with a modern GPU and sufficient system memory. Performance evaluation focuses on detection accuracy, tracking stability, and computational efficiency. The system is tested across multiple matches to ensure robustness and generalizability of the results.

III. RESULTS AND DISCUS SION

This section presents a detailed analysis of the experimental results obtained using the proposed football analytics framework. The results are evaluated from multiple perspectives, including object detection accuracy, tracking stability, team identification reliability, homograph projection effectiveness, and the quality of derived physical and tactical metrics. The discussion focuses on both quantitative performance and qualitative observations drawn from real match scenarios.

A. Object Detection Results

The object detection module demonstrates consistent performance across diverse match conditions. Players are detected reliably in both close-up and wide-angle shots, while referees and the ball are also identified with high confidence in most frames. Detection performance remains stable under varying illumination conditions, including daylight matches and floodlit night matches. In crowded regions such as the penalty box, the detector successfully identifies overlapping players, although occasional missed detections occur during extreme occlusions. The football, which occupies a very small area in the frame, is detected accurately during moderate motion. Detection failures are more likely during high-speed passes or long aerial balls, where motion blur and scale variation are prominent.

Nevertheless, these cases represent a small portion of overall match time and do not significantly affect downstream analysis.

B. Player Tracking Performance

The tracking module effectively maintains player identities across consecutive frames, enabling continuous trajectory extraction. Motion prediction al lows the tracker to handle short-term occlusions and abrupt changes in player direction. Trajectories remain smooth and temporally consistent, which is critical for accurate physical metric computation. Identity switches are infrequent and primarily occur during prolonged occlusions involving multiple players with similar appearance. In such cases, the tracker may temporarily lose identity consistency; however, re-identification typically occurs once players separate spatially. Overall, the tracking performances sufficient for both individual player analysis and team-level tactical assessment.

C. Team Identification Evaluation

Team identification based on jersey colour clustering performs reliably across most match scenarios. The use of HSV colour space improves robustness against lighting variation and shadow effects. Tem poral smoothing further stabilizes team assignments, preventing frequent label changes across frames. Misclassification is observed in limited scenarios where teams wear visually similar colour tones or when strong shadows alter perceived colour distributions. Despite these challenges, team identification accuracy remains high enough to support tactical analysis, such as formation assessment and zonal occupancy computation.

D. Homograph Projection Accuracy

Homograph-based field projection plays a crucial role in enabling metric analysis. The estimated trans formation accurately maps player positions from image space to pitch coordinates, allowing meaningful 5 G. Qualitative Observations interpretation of movement patterns. Projected trajectories align well with expected player locations on the field, validating the effectiveness of the homograph estimation process. Projection errors may occur when field markings are partially occluded or not clearly visible in the frame. These errors can lead to minor inaccuracies in speed estimation; however, the overall impact on long-term metrics such as total distance covered and heatmap generation is minimal.

E. Physical Performance Metrics

The computed physical performance metrics provide valuable insights into player workload and activity patterns. Speed profiles accurately reflect phases of high-intensity play, such as counterattacks and defensive recovery runs. Distance covered metrics align with typical match statistics reported in professional football analysis. Acceleration and deceleration patterns highlight periods of intense physical exertion, enabling identification of sprints and rapid directional changes. These metrics are particularly useful for sports science applications, including fatigue monitoring and injury risk assessment.

F. Tactical Analysis and Spatial Metrics

Spatial metrics derived from projected trajectories offer meaningful tactical insights. Player heatmaps clearly illustrate positional tendencies, revealing roles such as wide attackers, central midfielders, and defensive anchors. Zonal occupancy analysis high lights team strategies, including high pressing, com pact defensive blocks, and attacking overloads. Team-level metrics such as centroid movement and average inter-player distance provide an overview of formation stability and structural organization. Changes in these metrics over time correspond to tactical transitions, substitutions, and shifts in match momentum.

G. Qualitative Observations

Visual inspection of the generated analytics confirms that the system captures key aspects of match dynamics. Tracking visualizations with player trajectories and heatmaps enhance interpretability and facilitate intuitive analysis for coaches and analysts. The system's ability to operate on standard broadcast footage without specialized camera setups increases its practical applicability.

H. Computational Performance

The complete pipeline operates near real time on standard GPU hardware. Processing speed is sufficient to support post-match analysis and can potentially be optimized further for live match applications. The modular architecture allows performance bottlenecks to be addressed independently, ensuring scalability as more advanced models become available.

I. Comparative Discussion

Compared to traditional manual analysis and semiautomated systems, the proposed framework provides a more objective and scalable solution. While certain edge cases remain challenging, particularly under extreme occlusion, the overall performance demonstrates the feasibility of fully automated football analytics using deep learning and computer vision techniques. The results indicate that integrating detection, tracking, team identification, and spatial modelling within a unified pipeline significantly enhances the quality and consistency of analytical outputs

IV. CONCLUSIONS

This paper presented a comprehensive and fully automated football analytics framework that leverages modern deep learning and computer vision techniques to extract meaningful physical and tactical insights from broadcast football match videos. The proposed system integrates multiple key components, including object detection, multi-object player 6 tracking, team identification, and homograph-based field projection, into a unified and scalable pipeline capable of operating under real-world match conditions. The experimental results demonstrate that the proposed approach performs robustly despite the challenges inherent in broadcast footage, such as dynamic camera motion, frequent occlusions, varying lighting conditions, and scale variations. The object detection module reliably identifies players and the football across diverse scenarios, while the tracking component maintains consistent player identities over time, enabling accurate trajectory extraction. These trajectories form the foundation for subsequent physical and tactical analysis. By mapping image coordinates to real-world pitch coordinates, the system enables metric analysis that is both physically interpretable and comparable across matches. The derived metrics, including player speed, total distance covered, heatmaps, zonal occupancy, and formation-related indicators, provide valuable insights into player workload, positional behaviour, and overall team structure. Such information is critical for coaching staff, performance analysts, and sports scientists who require objective and repeatable evaluation tools. One of the key strengths of the proposed framework lies in its modular design. Each component of the pipeline can be independently improved or re placed as new algorithms and models emerge. This flexibility ensures that the system can evolve alongside advances in deep learning and computer vision research. Furthermore, the ability to operate on single-view broadcast footage significantly enhances the practical applicability of the system, as it does not rely on specialized multi-camera setups or proprietary tracking infrastructure. Although the system achieves strong performance, certain limitations remain. Extreme occlusions, rapid camera zooms, and visually similar team jerseys can still introduce errors in detection, tracking, or team identification. Addressing these challenges will require further research into more robust re identification techniques, multi-view fusion, and advanced temporal modelling. Nevertheless, the results presented in this work demonstrate that fully auto mated football analytics is both feasible and effective using current deep learning technology. Overall, the proposed football analytics framework represents a significant step toward scalable, objective, and data-driven performance analysis in football. The system has the potential to support a wide range of applications, including post-match analysis, player scouting, training optimization, and broad cast enhancement. By reducing reliance on manual annotation and subjective judgment, the framework contributes to more consistent and insightful football analysis.

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