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Football Match Analysis With Yolo

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Abstract: Football match analysis is an important task in modern sports analytics for evaluating player performance and tactical strategies. Traditional analysis methods depend on manual observation, which is time-consuming and subjective. This paper presents an automated football match analysis system using the YOLO (You Only Look Once) deep learning algorithm for real-time object detection. The proposed system processes football match videos to detect key entities such as players, referees, and the ball. YOLO performs single-stage detection by predicting bounding boxes and class probabilities in a single forward pass, enabling fast and efficient analysis.The model is trained on annotated football match datasets and evaluated using standard metrics including precision, recall, mean Average Precision (mAP), and frames per second (FPS). Experimental results show that the system achieves high detection accuracy with real-time performance, even in dynamic match conditions. The proposed approach reduces computational complexity compared to traditional methods and can assist coaches and analysts in performance evaluation and tactical decision-making.

I. INTRODUCTION

Football is one of the most widely played and watched sports in the world, generating a massive amount of visual data through broadcast and recorded match videos. Analyzing this data is essential for understanding player performance, team strategies, and match dynamics. Traditionally, football match analysis has been carried out through manual observation by coaches and analysts. Although effective to some extent, such methods are time-consuming, subjective, and limited in their ability to capture fine-grained spatial and temporal information throughout the game.With the rapid advancement of computer vision and deep learning, automated sports analytics has emerged as a promising alternative to traditional analysis techniques. Object detection plays a key role in football analytics, as identifying players, referees, and the ball is a fundamental step toward higher-level analysis such as player tracking, tactical evaluation, and performance assessment. However, football match environments are highly dynamic, involving frequent player interactions, occlusions, varying lighting conditions, and fast object movements, which makes accurate and real-time detection a challenging task.

Recent deep learning–based object detection models have shown significant improvements in accuracy and speed. Among these, YOLO (You Only Look Once) has gained considerable attention due to its ability to perform single-stage object detection in real time. Unlike traditional multi-stage detectors, YOLO processes the entire image in a single forward pass, enabling high-speed detection without sacrificing accuracy. This makes YOLO particularly suitable for real-time football match analysis, where quick and reliable detection is crucial.

In this paper, we propose an automated football match analysis system based on the YOLO framework. The proposed system processes match videos to detect and localize key entities such as players, referees, and the ball. By automating the detection process, the system aims to reduce human effort and provide consistent and objective analysis. The proposed approach can support coaches, analysts, and sports organizations in tactical decision-making and performance evaluation, while also serving as a foundation for advanced football analytics applications.

II. LITERATURE SURVEY

Paper 1 Title: Analysis of Player Tracking Data Extracted from Football Match Feed
Authors: Swetha Saseendran, Sathish Prasad Vetrivel Thanalakshmi, Swetha Prabakaran, Priyadharsini Ravisankar
Publisher / Journal: Romanian Journal of Information Technology and Automatic Control (2023)
Pros:This paper presents a comprehensive football analytics framework by combining YOLOv5 for player and ball detection with DeepSORT for multi-object tracking, enabling accurate extraction of player trajectories from broadcast videos. A major strength of this approach is its cost-effectiveness, as it removes dependency on expensive commercial tracking systems and wearable sensors. The inclusion of jersey color clustering allows reliable team identification, while camera calibration and perspective transformation convert 2D image coordinates into realistic pitch-level positions. Furthermore, the use of advanced analytical models such as pitch control, Voronoi diagrams, and expected

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threat (xT) provides deeper insights into player decision-making and tactical performance, making the system valuable for scouting and match analysis.
Cons:Despite its strong analytical capabilities, the system's performance is highly dependent on broadcast video quality and camera stability. The calibration and homography estimation process is complex and sensitive to errors, which may affect positional accuracy. Occlusion in crowded scenes can still cause tracking inconsistencies and identity switches. Additionally, the computational complexity of combining detection, tracking, and analytics makes real-time implementation challenging without high-end hardware, limiting its scalability in live match scenarios.

Paper 2 Title: Automated Player Identification and Indexing Using Two-Stage Deep Learning Network
Publisher / Journal: Scientific Reports (Nature), 2023
Pros:This study introduces a robust two-stage deep learning architecture that significantly improves player detection and identification in crowded football scenes. By employing a Detection Transformer for player localization and a secondary CNN for jersey number recognition, the system achieves high accuracy even under heavy occlusion. The automated indexing of players per play and synchronization with game clock data reduces manual annotation efforts and enables efficient video database management. The framework demonstrates strong quantitative performance and highlights the effectiveness of deep learning in handling complex broadcast video analysis tasks.
Cons:The two-stage design increases computational cost and inference time, making the system resource-intensive. Its reliance on high-resolution video limits applicability in low-quality footage. The method is primarily designed for American football, and direct adaptation to soccer requires architectural and dataset modifications. Jersey number recognition remains vulnerable to motion blur and partial visibility, which can reduce identification accuracy in fast-paced game situations.

Paper 3 Title: Referee Gesture Recognition Algorithm Based on YOLOv8s
Authors: Zhiyuan Yang, Yuanyuan Shen, Yanfei Shen
Publisher / Journal: Frontiers in Computational Neuroscience, 2024
Pros:This paper effectively applies YOLOv8s with multiple enhancements to address the challenging task of referee gesture recognition in football matches. The integration of a Global Attention Mechanism helps focus on relevant gesture regions while suppressing background interference. The addition of a P2 detection head improves recognition of small and distant gestures, and the MPDIoU loss function enhances bounding box precision. The proposed model achieves superior accuracy compared to baseline methods, making it suitable for applications such as VAR assistance, referee performance evaluation, and automated decision logging.
Cons:The system is limited to recognizing predefined gesture categories, restricting its scalability to new or complex gestures. Dataset preparation and annotation require significant manual effort. Performance may degrade in extreme lighting conditions or severe occlusion. Additionally, the scope of the work is limited to referee gesture recognition and does not contribute to holistic football match or tactical analysis.

Paper 4 Title: Football Match Analysis Using YOLO
Authors: Prof. S. M. Melasagare, Jeet S. Shile, Shashank J. Tipe, Amrapali R. Ballal
Publisher / Journal:Journal of Emerging Technologies and Innovative Research (JETIR), 2024
Pros:This paper presents a simple and practical approach to football match analysis using YOLO-based object detection combined with K-means clustering and optical flow techniques. The system successfully detects players, referees, and the ball, while estimating key performance metrics such as player speed, distance covered, and ball possession. Its straightforward architecture and clear methodology make it suitable for academic projects and beginner-level research in sports analytics. The approach demonstrates how computer vision can automate post-match analysis and reduce reliance on manual observation.
Cons:The proposed system lacks extensive experimental validation and benchmarking against state-of-the-art methods. Optical flow techniques are sensitive to camera motion and noise, which may reduce tracking accuracy. The approach struggles in crowded scenes and high-speed gameplay, and it is not optimized for real-time deployment. Tactical and strategic insights derived from the system remain limited compared to more advanced analytical frameworks.

Paper 5 Title: Object Detection and Tracking for Football Data Analytics
Authors: Shankara Narayanan V, Syed Ashfaq Ahmed, Sneha Varsha M, Guruprakash Jayabalasamy
Publisher / Conference: EAI Conference (IACIDS 2023), Published 2024
Pros:This paper provides a practical framework for football data analytics by integrating YOLO-based object detection with BYTETrack for stable multi-object tracking. The comparative evaluation of YOLOv5 and YOLOv8 helps justify model selection, and the system effectively estimates individual and team-level ball possession. The methodology is well-structured and demonstrates real-world applicability using football match footage, making it suitable for analytics-focused research and performance evaluation.

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Cons:The framework requires tactical camera footage, limiting its usability with standard broadcast videos. The analysis mainly focuses on ball possession and does not include deeper tactical metrics such as spatial control or decision-making evaluation. Performance degradation may occur in scenes with heavy occlusion and overlapping players. Additionally, the system demands considerable computational resources, which may affect scalability.

Paper 6 Title: Enhancing the Performance and Accuracy in Real-Time Football and Player Detection Using Upgraded YOLOv5 Architecture
Author: Keyan Zhao
Publisher / Journal: International Journal of Computational Intelligence Systems, 2024
Pros:This research proposes an upgraded YOLOv5 architecture incorporating SimSPPF and GhostNet modules to improve both detection accuracy and computational efficiency. The enhanced model effectively handles challenges such as occlusion, rapid player movement, and varying illumination conditions. Experimental results demonstrate improved precision, recall, and mean average precision compared to baseline YOLOv5 models. The approach is well-suited for real-time applications including live broadcasting, player monitoring, and automated football analytics.
Cons:The proposed architecture is complex and requires careful hyper-parameter tuning and large labeled datasets for effective training. Hardware dependency may limit deployment on low-resource systems. The study focuses primarily on object detection and does not extend to higher-level tactical or strategic analysis. Additionally, model interpretability remains limited, which can affect trust and explainability in analytical decision-making.

III. PROPOSED METHODOLOGY

The proposed methodology focuses on developing an automated and efficient football match analysis system using the YOLO (You Only Look Once) deep learning framework. The system is designed to detect and analyze key elements present in football match videos, such as players, referees, and the ball, in real time. The complete workflow of the proposed system is divided into several stages: video acquisition, frame extraction and preprocessing, YOLO-based object detection, post-processing, tracking and analysis, and result visualization.

1. Video Acquisition and Frame Extraction

The first stage of the proposed methodology involves acquiring football match videos from broadcast recordings or camera-based match footage. These videos serve as the input to the system. Since deep learning models operate on images rather than videos, the input video is decomposed into individual frames at a predefined frame rate. Extracting frames allows the system to analyze temporal changes in player movement and ball position throughout the match. The frame rate is selected carefully to balance computational efficiency and temporal accuracy.

2. Preprocessing

Each extracted frame undergoes preprocessing to make it suitable for the YOLO model. The frames are resized to match the input resolution required by the YOLO architecture. Pixel normalization is applied to scale the pixel values within a standard range, improving model convergence and detection accuracy. In some cases, data augmentation techniques such as rotation, scaling, and brightness adjustment may be applied during training to enhance the model's robustness against variations in lighting conditions, camera angles, and occlusions commonly observed in football matches.

3. YOLO-Based Object Detection

The core component of the proposed system is the YOLO-based object detection model. YOLO is a single-stage detector that treats object detection as a regression problem. It divides the input frame into a grid and predicts bounding boxes, confidence scores, and class probabilities for each grid cell in a single forward pass. This design enables YOLO to achieve high detection speed, making it highly suitable for real-time football match analysis.

The YOLO model is trained using an annotated dataset containing labeled instances of football players, referees, and the ball. During training, the model learns spatial features and object characteristics through convolutional layers. The training process minimizes a combined loss function that accounts for localization error, object confidence, and classification accuracy. Once trained, the model is capable of detecting multiple objects simultaneously within each video frame.

4. Post-Processing and Non-Maximum Suppression

After object detection, multiple bounding boxes may be predicted for the same object. To address this issue, Non-Maximum Suppression (NMS) is applied to remove redundant overlapping bounding boxes. NMS retains only the bounding box with the highest confidence score for each detected object, ensuring precise and accurate localization.

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5. Object Tracking and Match Analysis

The detected objects are tracked across consecutive frames to analyze player movements and spatial behavior during the match. Tracking enables the extraction of valuable insights such as player positioning, movement patterns, and interaction dynamics. These insights are crucial for tactical analysis and performance evaluation. The tracking process also helps maintain object identity consistency across frames.

6. Visualization and Performance Evaluation

In the final stage, the detection and tracking results are visualized by overlaying bounding boxes and class labels on the original video frames. This visual output provides an intuitive representation of the match analysis. The performance of the proposed system is evaluated using standard metrics such as precision, recall, mean Average Precision (mAP), and frames per second (FPS). These metrics demonstrate the effectiveness, accuracy, and real-time capability of the proposed methodology.

IV. WORKFLOW

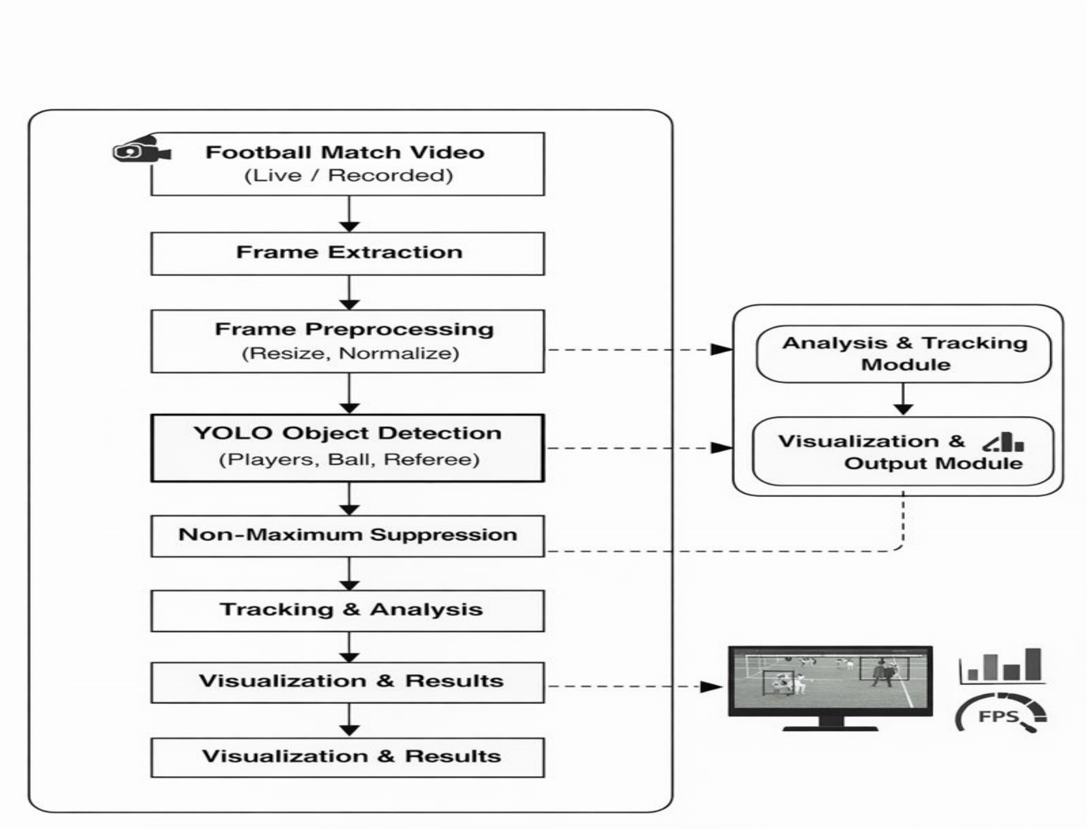

Fig. 1. System Workflow

The figure illustrates the system architecture of a YOLO-based football match analysis system. The process begins with input football match video, either live or recorded. The video is converted into frames through frame extraction, followed by preprocessing steps such as resizing and normalization. These frames are then passed to the YOLO object detection module, which detects players, the ball, and referees. Non-Maximum Suppression removes duplicate detections to improve accuracy. The detected objects are further processed in the tracking and analysis module to study movement and positions. Finally, the visualization and output module displays bounding boxes, performance metrics, and analytical results such as FPS and statistical insights.

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V. RESULTS

Fig. 2.

Fig. 3.

Fig. 4.

VI. CONCLUSION

In this project, we successfully designed and implemented a YOLO-based football match analysis system capable of detecting and analyzing important objects from match videos. We collected football video data, performed frame

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extraction, and applied preprocessing techniques such as resizing and normalization to improve model performance. The trained YOLO model was able to accurately detect players, the ball, and referees in real time. Non-Maximum Suppression was used to remove duplicate detections, improving accuracy and reliability. We also implemented object tracking to observe player movement and ball position across frames. The system generated visual outputs with bounding boxes, labels, and performance metrics such as FPS. Overall, the project achieved real-time detection and basic match analysis successfully, demonstrating the effectiveness of deep learning for automated sports analytics and reducing manual analysis effort.

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