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Football Match Analysis Using YOLOv5 for Player Detection and Tracking

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Abstract - In the modern era of data-driven sports analytics, football clubs and media broadcasters are increasingly adopting computer vision and artificial intelligence to extract actionable insights from match footage. This research presents a deep learning-based framework that utilizes the YOLOv5 object detection model for the automatic detection and counting of football players from video footage By leveraging pre-trained models and PyTorch frameworks, our system can process full match videos, annotate players in each frame with bounding boxes, and deliver count statistics in near real-time The proposed solution is lightweight, scalable, and suitable for both offline analysis and potential live-stream integration The system maintains robustness across various lighting and camera conditions and provides a baseline for further research in sports analytics automation

Key Words: Football Analysis, Player Detection, YOLOv5, Object Tracking, Sports Analytics, Computer Vision, Deep Learning.

1.INTRODUCTION

Football, a fast-paced and dynamic sport, generates vast quantities of visual data from every match. Traditionally, analyzing this data has been a manual and labor-intensive process, prone to human error and subjectivity. The advent of real-time object detection algorithms like YOLO (You Only Look Once) has made it feasible to automate critical tasks such as player counting, tracking, and formation detection.

This paper aims to bridge the gap between traditional sports video analysis and modern computer vision systems by demonstrating the effectiveness of the YOLOv5 model for detecting football players. The goal extends beyond simple detection to lay a foundation for more advanced analytical tasks.These include tactical pattern recognition, individual player performance evaluation, and the generation of real-time analytics to support commentators and coaches. By automating the fundamental task of player detection, this research seeks to unlock deeper strategic insights from game footage

II. RELATED WORK

Numerous methods have been proposed for sports analytics using computer visio. Early and prominent among these is the YOLO (You Only Look Once) algorithm introduced by Redmon et al., which revolutionized real-time object detection by processing images in a single pass through a neural networ While frameworks like OpenPose and MediaPipe are widely used for human pose estimation, they are not optimized for real-time detection in crowded and dynamic environments typical of football matches.

For player tracking, the Deep SORT (Simple Online and Realtime Tracking) algorithm, which builds upon object detectors like YOLO, has shown promise in assigning unique IDs to players .Other deep learning models, such as Convolutional Neural Networks (CNNs) and Region-based CNNs (R-CNNs), while highly accurate, often lack the real-time processing capabilities required for live sports analytics Recent benchmarks indicate that YOLOv5 achieves a superior balance of speed (measured in Frames Per Second) and accuracy (mAP@0.5) on the COCO dataset, making it an ideal choice for the live video analysis of sports where quick reaction time is critical[cite: 16].

III. METHODOLOGY

The methodology for this research is structured to address the challenges of manual player tracking, which is often tedious and unreliable in the fast-moving environment of a football match.

A. Problem Statement

Analysts and coaches require automated tools to perform the following tasks:
Automatically detect all players on the field
Maintain consistent performance across various environmental conditions, such as day or night matches and weather changes like rain.
Process full-length match videos without the need for manual, frame-by-frame supervision.
*Effectively handle challenges like overlapping players and real-world occlusions.

B. Objectives

The primary objectives of this research are to:
Build an automated system capable of detecting and counting football players in video footage.
Integrate the YOLOv5 model for real-time object detection.
Enhance video frames with visual annotations to aid in analysis.
Provide a modular and extensible codebase that can be used for further research and applications in sports analytic.

C. Dataset and Preprocessing

The model used in this research is pre-trained on the COCO dataset, which includes a "person" class suitable for detecting football players. The robustness of the COCO dataset allows for accurate detection in sports footage, provided the players are distinguishable from the background. Before being fed into the YOLOv5 model, each frame from the input video undergoes preprocessing. This involves resizing the frame and normalizing its color channels. Detections that are not relevant to the "person" class are filtered out.

D. System Architecture and Detection Pipeline

The system follows a sequential pipeline for processing video footage. The architecture is as follows:
1. Input Video: A standard football match video file is provided as input.
2. Frame Extraction: The video is broken down into individual frames for processing.

3. YOLOv5 Inference: The yolov5s (small) model, chosen for its high speed, is used for inference. The model is loaded with pre-trained weights from the Ultralytics PyTorch Hub.
4. Detection and Counting: The model processes each frame to detect players, outputting bounding boxes and confidence scores for each detection.The system is configured to only consider detections of class 0 ("person"). The total number of detected players in each frame is counted.
5. Video Annotation: Bounding boxes are drawn on the frames using OpenCV's cv2.rectangle() function, with labels indicating the confidence score. The player count is displayed on the top-left corner of each frame.
6. Output: The processed and annotated frames are compiled into a new video file..

IV. EXPERIMENTAL SETUP

The experiments were conducted on the following hardware and software configuration:
Hardware:
CPU: Intel i7
GPU: NVIDIA GTX 1660 Ti and Google Colab's Tesla T4
RAM: 16 GB
Software:
Python: 3.8
PyTorch: 1.12+
OpenCV: 4.5
YOLOv5: via PyTorch Hub and Ultralytics package
Video Input: 1080p match footage at approximately 30 FPS..

V. RESULTS AND DISCUSSION

The performance of the system was evaluated using several standard metrics, including Frames Per Second (FPS), mean Average Precision (mAP@0.5), recall, and precisio.

Evaluation Metrics:
Metric	Description
FPS	Frames processed per second
mAP@0.5	Mean Average Precision at an Intersection over Union (IoU) of 0.5
Recall	The percentage of actual players that were correctly detected
Precision	The percentage of detections that were actual players

Current Results:
FPS: Approximately 28 on GPU
Precision: 91.2%
Recall: 88.7%
mAP@0.5: 89.6%

The YOLOv5-based detection system performed effectively across a variety of match conditions. Players were consistently detected in different orientations, during various movements, and even with partial occlusions. he annotated videos provide analysts with valuable data, including accurate player counts per frame and a visual representation of player formations and movement patterns.

While the model was pre-trained on the general COCO dataset, for more specialized tasks, a custom model was trained using a football-specific dataset from Roboflow[cite: 108]. The training process, conducted over 80 epochs, showed a consistent improvement in performance, with the final validation achieving a mAP50-95 of 0.601 for all classes, and 0.801 specifically for the 'player' class. This demonstrates the model's capability to be fine-tuned for higher accuracy in a specific domain.

VI. FUTURE WORK

While the current system is effective, there are several limitations that offer avenues for future work. The system does not perform individual player identification (e.g., recognizing jersey numbers), differentiate between teams, or detect the ball or referees. It may also occasionally misidentify non-players like coaches as players.

Future enhancements could include:
Integrating Deep SORT for persistent player tracking with unique IDs.
Adding an Optical Character Recognition (OCR) module to read jersey numbers for player identification.
Fine-tuning the YOLOv5 model on more extensive football-specific datasets like SoccerNet or SportsMOT.
Developing an analytics dashboard to visualize data such as heatmaps, pass completion statistics, and team formations.
Extending support to other sports like cricket or basketball

VII. CONCLUSION

This research successfully validates the use of the YOLOv5 model for efficient, real-time player detection in football match footage The developed pipeline achieves a favorable balance between processing speed and detection accuracy, making it a viable tool for integration into larger sports analytics systems. By addressing the primary challenge of automated player detection, this work lays the groundwork for more sophisticated analysis. With planned enhancements in tracking, identification, and classification, this system has the potential to evolve into a powerful AI-driven tool for football strategy analysis and to augment live broadcasting with rich, data-driven insights

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