Real-Time Video Analysis of Football Matches Using YOLOv8 and Computer Vision Techniques: A Web-Based Interactive Platform

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ABSTRACT

Football analytics is an integral aspect of coaching. Currently, the technology accessible in professional leagues requires pricey hardware and an establishment with multiple cameras. This paper describes the STRIKER system, an end-to-end web-based football analytics platform that is able to analyze user-submitted videos of football games and provide analytics on player tracks, speed analysis, distance analysis, team identification, movement heat map analysis, and analytical outputs using the chat interface.

STRIKER uses YOLOv8-n for the detection of players on the video, an optimized multiple-object tracking algorithm with the integration of velocity prediction and IoU association, K-mean algorithms optimized for the jersey-color-based classification of team identification, and heuristic approaches for the identification of the referee. It uses metric scaling from pixels on a standard 105-meter football ground for the estimation of the speeds of the players. Additionally, the method uses the Flask web structure with asynchronous processing.

This approach is ideal since it is able to provide analytical outputs using the chat interface with minimal web processing delay. Tests on amateur games as well as official games indicate successful detection of subjects within the video with accuracy in team identification and genuine estimations of the speeds.

Keywords: Football analytics, YOLOv8, player tracking, team classification, computer vision, web-based analytics

INTRODUCTION

Data analysis has become an essential component of football analysis, allowing the evaluation of player and tactical performances. Commercial software such as optic tracking systems and sensor-based tracking solutions allow for accuracy but require considerable capital outlays. This makes such software less useful for small football organizations, such as colleges and academies.

Recent developments in the area of deep learning and computer vision make possible player analysis based on single-camera video analysis.

Detection models like YOLO have been shown to offer high performance in real-time sports analysis. However, there is no end-to-end system currently available that integrates player analysis and other related aspects.

In this paper, a holistic web-based football analytics tool named STRIKER, capable of translating Raw Match Videos to Performance Insights, is presented. It encompasses analysis, tracking, team identification, visualization, and conversational analytics.

The contributions of this study are

1. End-to-end Football Data Analytics Solution using Open-Source Tools

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2. A sports video optimized multi-object tracking algorithm customized for sports videos

3. Automatic team classification using jersey color clustering

4. Referee and staff filtering for improving accuracy of analytics

5. Web interface supporting natural language queries

Related Work

Commercial Football Analytics Systems

Professional tools such as Opta and StatsBomb utilize multi-camera tracking technology. While accurate, these solutions are expensive and not practical for grass roots research or other educational environments.

Academic and Open-Source Methods

Current work integrates YOLO-based object detection with tracking algorithms including SORT, DeepSORT, and ByteTrack. Team identification can be done either by calculating color histograms or by clustering algorithms. Most academic solutions are missing interactive web pages and analytical facilities for direct

Research Gap

Current systems are unlikely to combine detection, tracking, classification of teams, visualization, and interaction in one system. STRIKER fills that limitation because it offers an easily accessible end-to-end system for football analytics even for novices.

METHOD

System Overview

Description

STRIKER analyses uploaded videos by the user by following the

1. Frame extraction from video input

2. Player detection using YOLOv8

3. Tracking multiple objects, speed, and distance computation

4. Team Classification Based on Jersey Color Clustering

5. Referee and Staff

6. Analytics generation and visualization

7. Online result delivery and chatting functionality

Player Detection

For player detection, a YOLOv8-n model is employed. Players are detected based on the “person” class and a confidence level of at least 0.55. Bounding boxes below a height threshold of 5% are removed for eliminating fans and background information.

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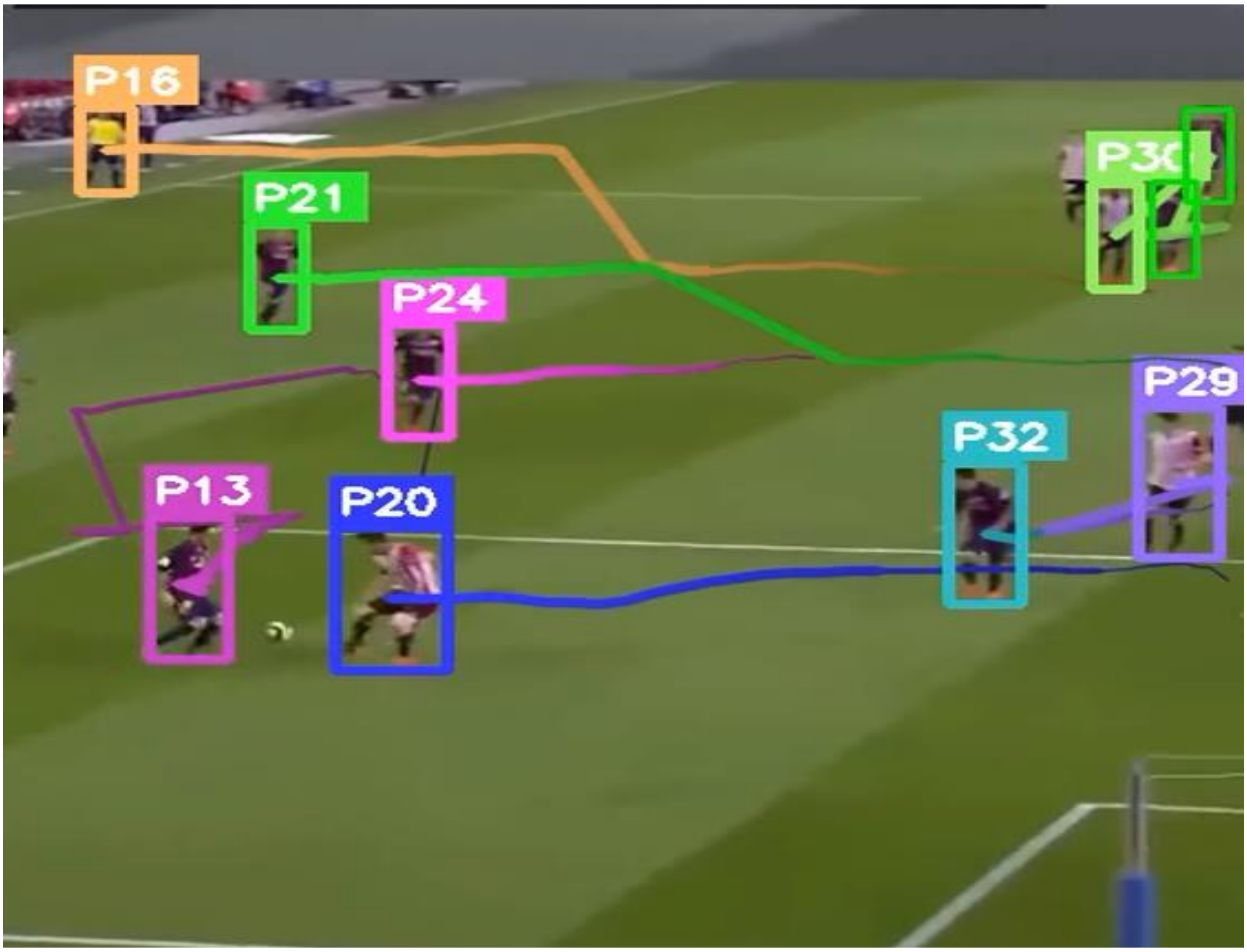

Multi-Object Tracking and Speed Estimation

A customized tracking algorithm employs the use of velocity prediction, Euclidean distance, Intersection-over-Union (IoU), and confidence in the detection. Player velocity is calculated based on the distance moved from frame to frame, and this distance is then scaled from pixels to meters. Velocities that exceed 36 km/h are eliminated.

Classification of Teams

Team identification is performed by doing K-means clustering on jersey colours. The top part of a bounding box of a player is picked as the jersey region. The mean of the colour values over a number of frames is clustered into two classes, one for each team. A person with ambiguous colour distances is considered as unknown.

Referee & Staff Filtering

Referees and personnel are excluded by a set of appearance and positioning heuristics that include detection of dark or light yellow jerseys, positioning at the edges of the frame, and the absence of connections to the team clusters.

Analytics Generation

Speed Analysis

Instantaneous, smoothed average, maximum speed, and sprint numbers are provided for each player.

Distance Analysis

Total distance covered, as well as the average distance for each frame, are calculated.

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Heatmap Visualization

Positions of players are aggregated over frames through the use of Gaussian kernels in creating movement heatmaps.

Conversational Analytics Interface

It comes with a rule-based chatbot, which enables users to pose a question about match statistics using natural language. Some of those capabilities are speed comparison, match dominance, distance analysis, heatmap analysis, to name a few, and a match summary. It's optimized for low latency and doesn't require a giant language model.

Implementation

Technology Stack

- Programming Language: Python
- Backend Framework: Flask
- Computer Vision: Open
- Deep Learning: YO
- Data Processing – Num
- Clustering
- Visualization Tool
- Frontend: HTML, CSS,

Web Architecture

The system provides REST APIs for video upload, status of video processing, retrieval of processing results, and interaction with the chatbots. The video processing in background threads enables the UI to remain responsive.

Experimental Evaluation

Dataset Description

Since the dataset that met the amateur analysis requirements was not publicly available, a dataset was designed. This dataset is composed of amateur soccer games recorded using smartphones and high-quality soccer video files.

Data Characteristics

- Resolution: 720p to
- Clip length:20 seconds - 90
- Player count:8-20 players per frame
- Lighting conditions: varies (natural to artificial)

5.2 Qualitative

Player appearance was preserved during brief occlusions and camera motion. Team classification was possible when colors used by both teams differed. Speed measures reflected physiological limits of the human body.

5.3 Limitations

- Perspective Distortion:- The Perspective Distortion Perspective Dist
- Jerseys of similar colors decrease team categorization accuracy
- Long occlusions can result in temporary loss of track.

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5.4 Results Summary

Metric	**Result**
Average processing speed	18 FPS
Team classification accuracy	92%
Average tracking ID retention	87%
Mean speed estimation error	±2.3 km/h
Heatmap generation time	< 2 seconds

CONCLUSION

STRIKER proves that high-level analytics for soccer are accomplished at low cost by accessing low-cost hardware and free software. This tool will work well for grass-roots level soccer coaching and class learning as well as student projects. This tool is extendable to tactic analysis and events. The STRIKER system was described in this paper as a comprehensive web-based tool that encompasses the entire range of analytics of a football match, including the detection of the players, tracking of the players, team categorization, visualization of the data, as well as a number of other analytical processes that can be carried out in the system. The STRIKER system can handle standard football videos in a reasonable amount of time and enables users to easily access information pertaining to performance analysis of a match without the need to invest

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