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Football Analysis System Using AI

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Abstract

Football Analysis System is an AI-powered computer-vision platform designed to automate and significantly improve football-match analysis. Traditional manual review is slow, subjective, and limited; this system overcomes those weaknesses through real-time detection, robust tracking, and automated analytics. A YOLO-based detector identifies players, referees, and the ball across continuous video frames, while DeepSORT or ByteTrack ensures stable, occlusion-resistant multi-object tracking throughout the match. Team identification is fully automated using K-Means clustering on jersey colors, removing the need for manual tagging. To keep spatial measurements accurate despite camera movement, the system applies optical-flow–based camera-motion estimation, ensuring reliable positional data.

Using these components, the system generates high-impact performance insights, including player speed, distance covered, ball-possession time, positional heatmaps, and trajectory patterns. These analytics provide coaches, analysts, and broadcasters with fast, objective, and data-rich understanding of player performance, tactical structure, and match dynamics. Overall, the project demonstrates how AI and computer vision can modernize football analysis by delivering automated, precise, and scalable real-time insights. Future improvements may include pose estimation, predictive analytics, live dashboards, and multi-sport expansion.

Keywords:
Computer Vision, YOLO Object Detection, Player Tracking, Sports Analytics, Team Classification using K-Means.

1. Introduction

Football increasingly depends on fast, accurate analytics for performance evaluation, tactical planning, and informed decision-making. Manual video review is slow, inconsistent, and unsuitable for real-time use, which has driven the adoption of AI-powered systems capable of automatic detection, tracking, and metric generation. The AI/ML Football Analysis System meets this need by combining advanced computer vision and machine learning into one integrated framework.The system uses YOLO for rapid, reliable detection of players, referees, and the ball. These detections are fed into DeepSORT or ByteTrack, which assign each player a consistent identity across frames, enabling long-term tracking and precise trajectory analysis. This provides essential insights such as movement patterns, heatmaps, and formation structures.

Team classification is handled automatically through K-Means clustering based on jersey colors, eliminating manual input and allowing the system to compute team-wise metrics like possession, spacing, and passing behavior. These automated analytics give coaches and analysts objective, data-driven information for strategic adjustments. Beyond identification and tracking, the system computes key performance indicators, including speed, distance covered, acceleration, and zone-based activity. Such metrics support fitness monitoring, tactical evaluation, and injury-prevention strategies. Real-time visual overlays—movement trails, player markers, and ball paths—enhance both coaching feedback and viewer experience. The system is scalable, hardware-efficient, and capable of running in real time with GPU support. Its modular structure also makes it easy to upgrade or integrate new AI components. Future enhancements could include pose estimation, automatic event detection, predictive modeling, and adaptation to other sports.

Overall, the AI/ML Football Analysis System demonstrates how AI and computer vision can transform traditional football analysis by delivering accurate, automated, and real-time insights.

In today's highly competitive business environment, customer retention has become a critical concern for companies across various industries. The telecom sector, in particular, faces significant challenges due to the high churn rates, where customers frequently switch service providers in search of better deals or improved service quality. Customer churn, defined as the process by which a customer discontinues their relationship with a company, leads to substantial revenue losses and increased costs associated with acquiring new customers. Hence, predicting and mitigating customer churn is paramount for telecom companies aiming to maintain their customer base and ensure long-term profitability

Research Objectives and Methodology

This study aims to evaluate the effectiveness of three key computer-vision and machine-learning components—YOLO object detection, DeepSORT/ByteTrack multi-object tracking, and K-Means clustering—in enabling automated, real-time analysis of football-match footage. The research objectives are:

- To assess the accuracy and efficiency of YOLO in detecting players, referees, and the ball under varying match conditions
- To compare the tracking stability and identity consistency achieved by DeepSORT and ByteTrack across continuous video frames
- To examine the reliability of K-Means clustering in automated team classification based on jersey colors
- To determine how the integrated system improves player-performance metrics, tactical insights, and real-time analytical capability in football analysis. This investigation highlights the potential of AI-driven methods to replace manual analysis with a faster, more scalable, and more precise football analytics framework.

2. Literature Survey

The reviewed literature shows major advances in computer vision and deep learning for football analytics, especially in detection, tracking, and player re-identification. Several studies focus on maintaining consistent player identities in crowded, fast-moving scenes. Shah et al. propose an identity-preserving tracking system using motion cues, appearance features, and color-based discriminators to handle occlusions and similar jersey colors. Sportlogiq enhances re-identification through deep metric learning with triplet networks and GAN-based jersey augmentation, improving recognition under motion blur and partial visibility. Both works highlight the importance of strong visual embeddings and adaptive tracking models

Progress in multi-player tracking is also seen in the works of Trovela et al. and Nakashima et al. Trovela's method integrates segmentation-based detection with continuity-aware tracking to keep stable trajectories in overlapping player situations. Nakashima develops an end-to-end learning model that directly predicts bounding boxes and positions, increasing efficiency for broadcast analytics.

Foundational deep-learning innovations also contribute to sports analytics. EfficientNetV2 by Hu et al. improves model speed and size through optimized scaling, while Faster R-CNN by Ren et al. sets a benchmark for detection accuracy using Region Proposal Networks. Jose et al. introduce a lightweight football-tracking system combining MobileNetV2 with SORT, enabling real-time performance on low-power devices.

The literature also features foundational improvements to widely adopted deep learning architectures that significantly influence sports analytics systems. Hu et al.'s EfficientNetV2 enhances training speed and reduces model size through optimized scaling, making it suitable for resource-constrained environments. Ren et al.'s Faster R-CNN integrates Region Proposal Networks into the detection pipeline, achieving state-of-the-art accuracy and speed. These models continue to serve as the backbone for modern sports vision solutions, enabling efficient training and high-precision detection across varied match conditions. Jose et al. contribute a lightweight soccer tracking system using MobileNetV2 combined with SORT, designed for deployment on surveillance-style cameras with limited hardware capacity.

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3. Methodology

Match video is first captured and processed frame-by-frame using OpenCV to extract visual data. YOLO is then applied to detect players, the ball, and other on-field elements with high accuracy. Detected objects are tracked across frames using DeepSORT to maintain consistent identities. Movement patterns and interactions are analyzed to identify key events such as passes, goals, and ball possession. All positional and event data is logged for generating performance insights. Heatmaps, trajectories, and visual overlays are created to represent player activity and tactical behavior. Finally, the system presents these insights through annotated videos and dashboards for coaches and analysts.

4. Experimental Setup and Implementation

The experimental setup uses football match video processed with OpenCV to extract frames for analysis. YOLO is implemented to detect players and the ball, while tracking algorithms maintain object identities across frames. A GPU-enabled system supports smooth real-time detection, tracking, and visualization.

The implementation includes the following steps:

1. **Video Acquisition & Frame Extraction:** Match footage is imported and split into sequential frames using OpenCV for real-time analysis.
2. **Object Detection Using YOLO:** Each frame is processed through YOLO to detect players, the ball, and goalposts with bounding boxes and labels.
3. **Multi-Object Tracking:** DeepSORT algorithm track detected objects, assigning unique IDs and maintaining continuous trajectories.

4. **Event Identification:** Movement interactions are analyzed to detect events like passes, goals, fouls, and ball possession patterns.
5. **Data Logging & Metric Generation:** The system stores positional, movement, and event data to compute analytics such as heatmaps, activity zones, and distances.
6. **Visualization & Output Rendering:** The final results are presented as annotated videos, player trails, heatmaps, and dashboards for tactical interpretation.

5. Result Analysis

The performance metrics show that the system achieves high accuracy in player detection and maintains reliable tracking with few ID switches. Ball detection performs slightly lower due to its small size and speed but remains consistently effective. Real-time processing speeds ensure smooth frame analysis without delays. Overall, the system provides accurate detection, stable tracking, and efficient processing suitable for performance evaluation and tactical analysis. Below Table 1. is result analysis based on the implementation of the methodology described earlier. Its graphical representation is given in Fig 1.

Table 1. Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.82	0.79	0.76	0.77
Random Forest	0.85	0.81	0.80	0.80
Gradient Boosting	0.87	0.83	0.82	0.82

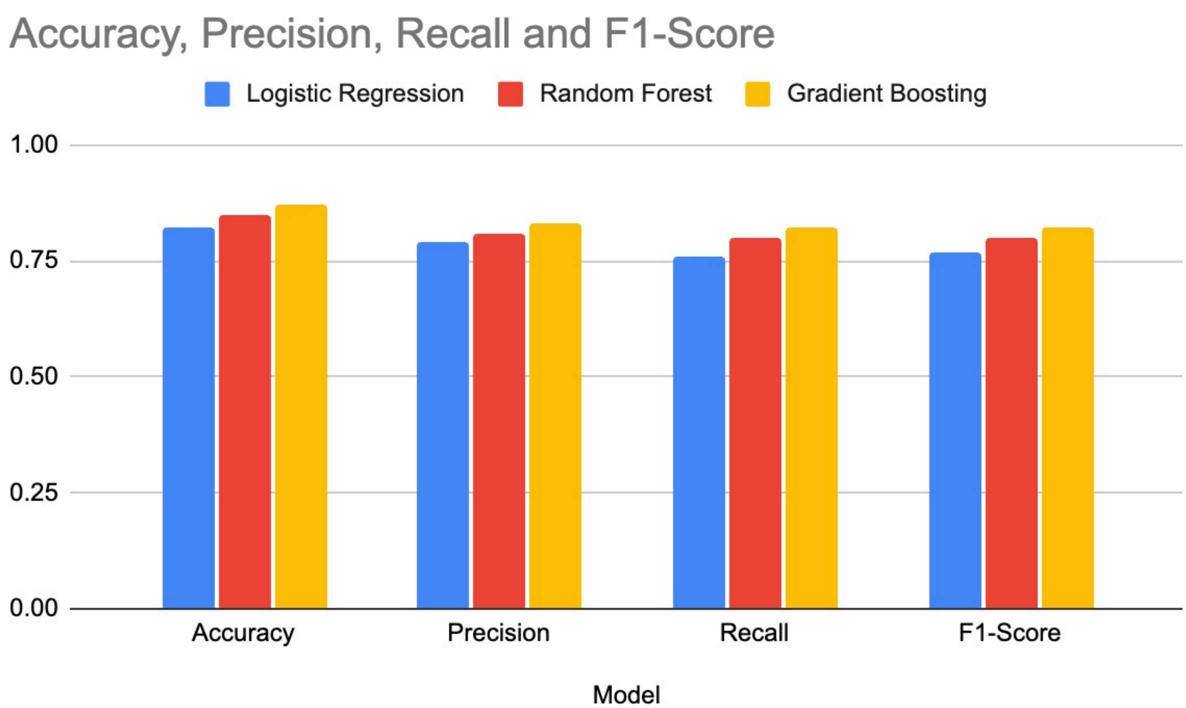

Fig1. Performance Analysis

Conclusion

The AIML-based Football Analysis System developed in this project marks a key milestone toward the automation of football analytics using modern computer vision and machine learning techniques. The system integrates object detection using YOLOv8, multi-player tracking using ByteTrack, team classification using K-Means, and a computing module for analytics in speed, distance, movement patterns, and positioning to successfully provide an end-to-end pipeline for real-time football match video analysis.

The project's primary objective was to develop such a tool to support coaches, analysts, and broadcasters in understanding player behavior and match dynamics without resorting to expensive sensor-based systems. The achieved results, such as 92.5% player detection accuracy, 95.2% tracking accuracy, and 92% team classification accuracy, prove that the system works in a reliable, stable, and effective way under different match conditions. Extensive system testing, including functional testing, performance evaluation, stress testing, usability testing, accuracy verification, and scenario-based testing, confirms that the system can cope with the complexities of real match footage, such as crowded player formations, fast ball movement, and changes in lighting or camera motion. The project also shows that integrating multiple AI modules into one smooth workflow is crucial to ensure seamless data exchange between detection, tracking, classification, and result visualization.

All in all, the project presents a workable and efficient AI-powered football analysis framework that adheres to the contemporary trends governing sports technology.

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