SoccArt - Soccer Game Analysis

Aditya Gupta* **Armaan Khetarpaul*** **R. K. Shishir***
Sahil Chaudhary* **S. Sharath*** **Umang Majumder***

Indian Institute of Science

{adityapg, armaank, shishirr, sahilc, ssharath, umangm}@iisc.ac.in

Abstract

This paper presents an automated computer vision pipeline for Soccer game analysis using a video input. The system employs YOLOv10 and ByteTrack for robust detection and tracking of players, referees, and the ball. Team identification and jersey number recognition are achieved through SigLIP-based color clustering and neural networks like ResNet34 and ViTPose. Field-Camera calibration and homography transformation map detected entities onto a minimap. Interpolation with sliding window smoothing ensures temporal consistency. The pipeline provides accurate positional data and annotations, enabling detailed gameplay analysis and insights into soccer strategies. The code for our work can be found at https://github.com/adityapgupta/Sports-Analysis

1 Introduction

Automated soccer game analysis plays a crucial role in coaching, broadcasting, and fan engagement. However, existing solutions often lack integration. They rely on outdated techniques that fail to provide a complete, robust pipeline for tasks such as player tracking, team identification, and ball detection. To address these limitations, we present a state-of-the-art, end-to-end pipeline for soccer analysis. Our system combines YOLOv10 for detection, ByteTrack for tracking, and models like ResNet34 and ViTPose for jersey number recognition. Integrated with field-camera calibration and homography, it delivers accurate positional and identity data, enabling comprehensive game analysis in real-time. SoccerNet dataset is used for training. (1) (2)

2 Methodology

Our proposed pipeline integrates state-of-the-art models and techniques to deliver an end-to-end solution for soccer game analysis. The system operates in the following stages:

1. **Detection and Tracking:** Video frames are processed using YOLOv10 (3) to detect players, referees, and the ball. ByteTrack is employed for multi-object tracking, ensuring continuity of object identities across frames.
2. **Team Identification:** Detected players are assigned to teams using SigLIP (4), which clusters players based on their clothing. Goalkeepers are identified by checking their distance from the centroid of both teams.
3. **Jersey Number Recognition:** Player identification is achieved through jersey number recognition (5). Models like ResNet34 and Vision Transformers for Pose Estimation (ViTPose) are used for this purpose.
4. **Calibration and Homography:** Keypoints on the field are detected using models from *No Bells Just Whistles* (6) to map 3-D camera coordinates to a 2-D plane. A transformation matrix learned from this mapping is used to perform homography on all detections. The resulting 2-D map of the field is utilized for analysis.

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5. **Interpolation and Smoothing:** The ball's position is estimated through interpolation to account for detection inconsistencies. A sliding window frame smoothing approach is applied to both ball and player trajectories to reduce noise and jitter in the final detection.
6. **Analysis:** 2-D map data is used to analyze player and ball movements throughout the game. Metrics like sprint patterns, ball possession, and passing opportunities are calculated to provide tactical feedback. Team formations are visualized through Voronoi diagrams.

3 Results

1. **Player Tracking:** Player tracking performance is quantified using the Average Precision (**AP**) metric at IoU threshold of 0.5, evaluated on the SoccerNet 2023 Player Tracking Dataset. As shown in Table 1, our model demonstrates superior performance compared to existing open-source player tracking models.

Table 1: Player Detection AP Score at IoU threshold = 0.5

Model	**AP**
YOLOv5 Based (7)	0.810
YOLOv8 Based (8)	0.794
YOLOv10 Based (Ours)	**0.862**

2. **Jersey Number Recognition:** The model's performance on jersey number recognition is evaluated using Accuracy (**Acc**) on the SoccerNet 2023 Challenge Set. As shown in Table 2, while not the top performer, the model achieves a respectable 6th place on the SN-2023 Jersey Number Recognition accuracy leaderboard.

Table 2: Jersey No. Recognition Accuracy (9)

Model	**Acc (%)**
ZZPM	**92.85**
AIBrain Global Team	75.18
PARSeq & VitPose Based (Ours)	79.31

3. **Calibration:** The metric evaluates re-projected keypoint accuracy within 5 pixels (*acc@5*) and the completeness ratio (*CR*), representing the fraction of images with detected keypoints. The Final Score (**FS**) is calculated as $CR \times acc@5$. On the SoccerNet 2023 Test Dataset, No-Bells-Just-Whistles slightly outperforms the 2023 SN-Calibration winner, as shown in Table 3.

Table 3: Calibration Metric Score

Model	*acc@5*	*CR*	**FS**
SAIVA_Calibration (9)	-	-	0.52
Sportlight (10)	**0.766**	0.734	0.56
No-Bells-Just-Whistles (6)	0.737	**0.775**	**0.57**

4 Conclusion and Discussions

This work presents a robust, integrated pipeline for automated soccer game analysis, using state of the art models. The system achieves superior player tracking (**AP** 0.862) and competitive calibration (**FS** 0.57), enabling detailed game play insights. Despite these advances, areas for improvement include refining jersey number recognition accuracy and expanding adaptability across varied datasets and camera setups. Future efforts can also focus on real-time analytics and enhanced visualizations for broader usability. Overall, this work establishes a strong foundation for advancing sports analytics through state-of-the-art computer vision techniques.

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