

Re-Identification Sports Analytics

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Abstract—Sports analytics is progressively using automated systems to comprehend player performance, team strategy, and game dynamics. Nevertheless, due to frequent occlusions, similar player appearances, and the fact that players may leave and re-enter the camera's field of view, it is still difficult to accurately track football players and keep their identities consistent throughout the match. In this paper, we introduce a Re-Identification based Multi-Object Tracking method that can track all the players, referees, the ball on a football field, and also maintain unique and consistent IDs throughout the match. The method includes object detection and person re-identification, which are not only used to detect players but also to identify them even after a temporary loss of visibility. By using a color-based jersey classification, it becomes possible to separate the players of different teams accurately along with the help of re-identification. Hence, the correct distinction of the players is made. The comparative evaluation has shown that the proposed method enhances identity consistency and lowers the number of ID-switch events in a better way than the standard tracking methods. The presented system offers the means for tactical analysis, acquiring performance insights, substitution tracking, and referee monitoring. Coaches, professional teams, analysts, and sports broadcasters can all benefit from the system, which can be set up at live matches by means of broadcast video streams. The forthcoming tasks will be on enhancing the precision of the ball tracking and modifying the model for real-time multi-camera sports settings.

Index Terms—Sports Analytics, Player Re-identification, Multi-object Tracking, YOLOv11, Appearance Features, Team Classification, Computer Vision.

I. INTRODUCTION

Sports analytics is progressively changing the way football teams measure performance, optimize strategies, and make data-backed decisions. The modern analytics framework is largely dependent on precise player tracking that opens the doors to innumerable insights like player positioning, movement patterns, formation utilization, and ball possession dynamics. Usually, such an analysis was done by hand through a thorough examination of the match footage, which is a time-consuming, subjective, and inconsistent yielding process. Recently, the improvement in computer vision and deep learning technologies has led to the rise of automated tracking systems as a viable alternative. Still, the task of getting dependable tracking in real-life football situations is not solved yet.

The most significant problem is how to keep the correct and consecutive identity of each player during the entire game. Football is about fast and continuous motions, close and heavy physical interactions, frequent occlusions, and variable camera

angles. What is more, players in the same team wear identical jerseys, thus, even for the main visual features, discrimination is difficult. Standard tracking techniques frequently lose the trace of the player when he is out of the frame or gets occluded and wrongly give the new ID to the player when he appears again. This results in ID changes, which lowers the accuracy of the analytics outputs and limits the extent to which automated tracking systems can be utilized.

Problem Statement:

Although there have been improvements in sports analytics, multi-object tracking systems that are currently available still find it hard to maintain a consistent identity of football players, referees, and the ball and even more so when they leave and are later allowed to re-enter the field of view. The most significant factors causing complexities are the players' similar looks, continuous occlusions, and the following of the broadcast camera by a moving and changing shot. There is a demand for a strong system that can guarantee identity persistence and distinguish players according to team affiliation.

Objectives of the Study:

An endeavor to create a mechanism that is capable of locating and following the movements of all the players, referees, and the ball throughout the course of the game.

Using Re-Identification methods to ensure that each player is assigned a unique and consistent ID, even if the player temporarily disappears from the camera view.

By means of jersey color classification, the players are grouped according to their respective teams.

Providing the tracked data that are accurate enough to be used for tactical analysis, player performance evaluation, and game strategy assessment is the objective as well.

To accomplish these goals, this research introduces a Multi-Object Tracking system based on Re-Identification that combines object detection with deep Re-ID feature learning. The model not only assures identity recognition but also code words for grouping teams. This novel approach readily translates into professional match analysis, team coaching, broadcast enhancement, and sports research.

II. LITERATURE REVIEW

Computer vision has been merged with machine learning in sports analytics, and the growth has been massive considering that teams and analysts are always looking for ways to automate the process of performance evaluation, tactical organization, and match dynamics.

TABLE I: Literature Review on Player Tracking and Re-Identification Techniques

Author / Year	Method / Model Used	Key Contribution	Limitation / Gap Identified
Bialkowski et al., 2014	Spatiotemporal Player Tracking	Revealed tactical patterns and team formations using tracking data	Does not maintain persistent identity across time
Bewley et al., 2016 (SORT)	Kalman Filter + Hungarian Algorithm	Introduced fast real-time tracking	Performs poorly during occlusion/re-entry, causing ID switches
Wojke et al., 2017 (DeepSORT)	SORT + Appearance Embeddings	Improved identity consistency in object tracking	Confused by visually similar players (same jerseys)
Zhong et al., 2020 (OSNet)	Omni-Scale Feature Learning Re-ID	Extracts strong discriminative features for re-identification	Accuracy decreases under low-resolution match footage
Cioppa et al., 2019 (SoccerNet)	SoccerNet dataset + Team classification	Enabled soccer-specific player/team recognition	Jersey color changes under lighting; numbers often unreadable
Lucey et al., 2014	Ball and tactical analysis	Highlighted tactical value of ball movement	Ball is small + fast → difficult to detect reliably
Ye et al., 2021	Survey of Re-ID techniques	Provided roadmap for improving identity consistency	Does not address football-specific multi-camera broadcast issues

One of the very first studies in this field was heavily dependent on event-based statistics that represent the number of passes, shots, or goals, for example. The problem with such event data is that they only reveal the spatial and strategic aspects of the game to a very limited extent. Henceforth, Bialkowski et al. (2014) found the void, presenting one of the first extensive analyses of soccer matches using spatiotemporal tracking data for extracting tactical patterns, team formations, and movement flows. Their project proved that there is enormous potential in using the continuous tracking method; however, it focused less on the problem of identity retention during complicated motion and occlusion.

Conventional Multi-Object Tracking (MOT) techniques, especially SORT by Bewley et al. (2016), resorted to a quick and minimalist tracking method with the help of the Kalman filter for motion prediction and the Hungarian algorithm for data association. Though it achieves high performance, SORT is subject to identity fragmentation since the tracked entities that leave and then re-enter the field of view cannot be recognized. A typical situation in football where long camera pans and the obstruction of players are standard. Wojke et al. (2017) in DeepSORT added deep appearance embeddings to the tracking process to bring in more identity stability. Thus the tracker became capable of matching the visual features from different frames, which minimized identity switching. But when players wear the same uniforms as in football, visually similar, and all the players from one team are wearing almost identical jerseys, then DeepSORT is at its weakest.

There was a shift of attention toward the development of Person Re-Identification (Re-ID) systems because of this. Re-ID models are designed to learn the discriminative features that do not change even under different visual conditions. OSNet, a concept introduced by Zhong et al. (2020), is a Re-ID model that learns multi-scale feature representations and, therefore, is highly efficient in differentiating between persons with minor visual differences. The features of the close body, the posture, and the gait of the person are some of the things that even in the case of the similar jerseys, provided that the players are in football, OSNet can spot them. Nevertheless, the performance of the Re-ID model deteriorates if the quality of the footage is poor or if the camera is positioned at a great distance.

Besides that, precise team identification is as equally important in player tracking as any other factor. Cioppa et al. (2019) came up with the idea of the SoccerNet dataset that is made up of the footage of the matches with annotations

comprising jersey numbers and team labels. Through their work, they illuminated the efficient methods of jersey color segmentation; however, jersey number recognition is still very unreliable in broadcast footage mainly due to the presence of motion blur and the distance between the camera and the player. The use of jersey color clustering aids in the separation of the players by the team, which is very important for the performance analytics that are, for example, team formation tracking and pass network extraction.

On the other hand, tracking the football is not an easy task at all. The problems are that the football is much smaller than the other objects, it travels very fast, and the players are blocking it most of the time. Lucey et al. (2014) not only emphasized the analytical worth of following the ball trajectory with respect to the player positioning but at the same time they admitted that dependable ball tracking requires high temporal and spatial resolution. Even though modern object detectors like YOLOv11 have gone a long way towards increasing the precision of small object detection, it is still far from being an easy task to constantly keep track of the ball's identity in every frame and even during occlusions.

Recent comprehensive reviews on Re-Identification such as the one by Ye et al. (2021) focus on the issue of coherence of the identity across multiple camera environments and this is the problem that is mainly addressed in the context of professional match broadcasts that use different camera angles. The report suggests that in the future sports analytics systems will be able to benefit a lot by having Re-ID integrated with multi-camera calibration.

III. SYSTEM ARCHITECTURE AND ALGORITHMS

The proposed system implements a tracking-by-detection methodology, where each frame of the video is independently analyzed to detect players, referees, and the ball, and then the detected entities are tracked to assign them consistent IDs. The system design is composed of four main units: Video Input & Preprocessing, Object Detection, Player Re-Identification & ID Assignment, and Team Classification & Output Tracking.

1. Video Input and Preprocessing

The data source is either a live or a recorded video of a football match. The frames are taken from the video at a set frame rate (normally 25–30 FPS). To achieve better detection results, some basic preprocessing steps like resizing and denoising are also carried out. If necessary, the camera movement could be stabilized and the playing field detected so that even when the camera is moving, the tracking will be more stable.

2. Object Detection Module

With the help of this unit, the system localizes all the desirable subjects in the football field. To achieve this, the system uses a deep-learning-based object detector (e.g., YOLO) to locate:

- players
- referees
- ball

By utilizing YOLO, the location is achieved through the creation of bounding boxes for all the characters in a single frame of the video. In this way, they are securing that even in the case of a fast movement or partial occlusion, the object is still detectable.

3. Player Re-Identification and Tracking Module

Just the result of an object detection is not enough for a player-tracking purpose. Because of that they employ a re-identification (Re-ID) model such as OSNet. The model takes the visual signatures and then converts them into feature embeddings for the detected players.

A Multi-Object Tracker (e.g., DeepSORT) is consequently implemented to:

- Predict player movement with a Kalman Filter
- Compare feature similarity and bounding-box overlap of current-frame detections with those of previously identified players to find the best match
- Keep the unique ID of each player consistent

Therefore, the system is able to remember and reassign the use of the same ID if the player disappears and then reappears in the frame thus, the number of ID-switch errors is notably reduced.

4. Team Classification Module

The system lets the user distinguish the single player teams by analyzing the color of the jersey. The area with the player's jersey is cut out and then changed into color HSV. By using color clustering or a simple classifier, the players get the labels of Team A, Team B, or Referee.

Such a classification is being secured through the use of the smoothing technique over a number of frames that helps in the disappearance of sudden changes in lighting.

5. Output and Analytics

The final output is made up of:

- The bounding box for each player
- Unique, persistent ID
- Team label
- Position of a ball and the estimated possession.

Such information can be used for producing heatmaps, player movement paths, team formation patterns, and tactical decision analysis.

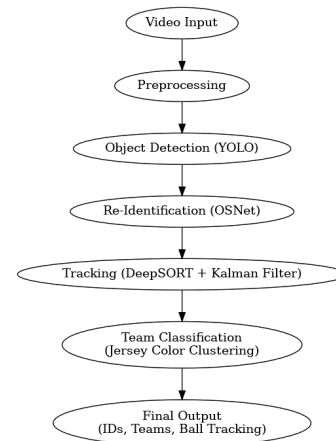


Fig. 1: System Architecture

Algorithms Used

(1) Object Detection Algorithm

Real-time detection is done by YOLO (You Only Look Once).

Steps:

1. The YOLO model is fed with the input frame
2. YOLO locates the objects in the image and predicts the class labels
3. Confidence thresholding gets rid of the uncertain detections
4. Non Maximum Suppression ensures that only one box per object is left

(2) Tracking and Identity Assignment Algorithm

DeepSORT is employed for Multi-Object Tracking.

Steps:

1. For each detected player, generate an appearance embedding via OSNet
2. Estimate the Kalman Filter's track locations for the previous frame
3. To generate a cost matrix for matches between detections and tracked IDs, use:

- Distance between bounding boxes
- Similarity of embeddings

4. Implement the Hungarian Algorithm to find the best assignment

5. Track updates are done for the matched IDs, new tracks are initialized for the unmatched detections, and players who are temporarily absent are marked instead of being removed immediately

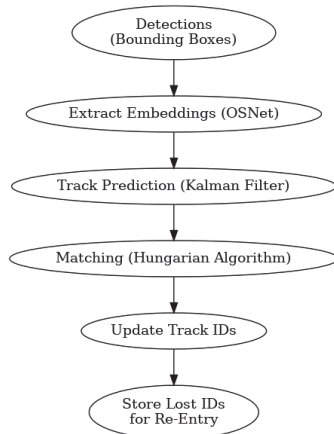


Fig. 2: Tracking Algorithm's

(3) Player Re-Identification Algorithm

With the help of the OSNet model, an appearance embedding vector is created, representing the player's visual features. The main idea is:

If the embeddings of two players are very similar, then it is highly probable that they are the same player. That is why the system keeps showing the same player's face even after they get occluded.

(4) Team Classification Algorithm

- The first step is to extract the jersey section from the bounding box.
- The next step is to convert the image to HSV color model (better color separation than RGB).
- Then K-Means clustering is used to group the pixels with similar colors.
- After that, the cluster groups are assigned to Team A, Team B, or referees.
- The last step is to smooth the predictions over the last N frames.

IV. MAJOR CHALLENGES

1. High Player Density and Occlusion

Football is a game that requires players to be very close to each other, and at times, players tend to group tightly around squares such as corners or free-kicks. The players physically block the camera's view of each other, which results in cases of partial or full occlusion. Hence, the tracking algorithm finds it challenging to keep the correct identity of the players, which is why ID switches are usually the most common occurrences.

2. Players Looking Alike from the Same Side

All players within a team dress in the same jersey, shorts, and socks. Consequently, the use of conventional visual features becomes insufficient for the differentiation of individuals. Minor visual differences (walking style, posture, body features) need to be considered by Re-ID models, which is a difficult task especially when the players are in motion, there is some blur, or the image is of low resolution.

3. Changing and Camera Movement

The broadcast cameras are not static as they frequently zoom, pan and change the angle of the shot. This alters

the size and view of the players on the screen. Tracking methods that solely rely on bounding boxes are not effective in such scenarios unless they are also supported by a strong appearance and motion model.

4. Players Going Out of the Camera Frame and Later Returning

Players on the field may walk or run off the camera view during the match. At the moment of their return, the system must be able to accurately give them back their previous identity. If there are no effective Re-ID and memory features, then this situation is often the cause of identity resets.

5. Small and Quick Ball Tracking

The ball is a small object, it moves very fast and is quite often visually blurred. Also, the ball may look like the ground or player uniforms if the lighting is a certain way. Therefore, the task of the ball is to be detected and tracked, which is much more difficult than the tracking of players.

6. Lighting Change and Shadow Effects

Since the outdoor stadiums are open, variable lighting conditions are always a possibility due to the sun, the floodlights, and the shadows falling in different parts of the field. These factors influence jersey color classification as well as appearance embedding consistency.

7. Referee Differentiation from Team Players

The referees' clothing may at times be similar in color to one of the teams. Without the presence of definite referee detection logic, they will be considered as part of the team, which will have an impact on tactical analysis and the accuracy of team assignment.

8. Real-Time Processing Constraints

The sports analytics systems have to handle the video frames either in real-time or near-real-time. The simultaneous execution of object detection, re-identification, tracking, and team classification is a heavy task that demands very well-optimized models and hardware acceleration. The major challenge that lies here is to be able to maintain accuracy while still being fast.



Fig. 3: Player Tracking

V. STRATEGIES TO OVERCOME THESE CHALLENGES

1. Handling Occlusion and Player Crowding

- In case bounding boxes are barely visible, one can use re-identification (Re-ID) embeddings to connect the player's face with the identity.
- For the moment, when there is a temporary occluded area, the player can be located with the help of Kalman Filter-based motion prediction.
- Short-term memory of tracks is the way that players should not be immediately taken out of the screen when they are lost for a few frames.

2. Differentiating Players with Similar Appearance

- Employing OSNet-based Re-ID is the feature that recognizes the fine-grained visual features of the person such as gait and body, not just the color of the jersey.
- Turn on data augmentation (blur, lighting changes, zoom) so that broadcast conditions will not affect the model.
- With the help of part-based feature pooling (e.g., upper torso only) one can concentrate on uniquely visible features.

3. Dealing with Dynamic and Moving Cameras

- Camera motion compensation is feasible by means of feature matching and homography estimation which are utilized for scene stabilization.
- Image coordinates are changed into field coordinates (pitch mapping), which gives the spatial consistency both during zoom and pan.
- Temporal smoothing filters are used to soften the abrupt trajectory changes.

4. Re-Identifying Players After Leaving and Re-Entering Frame

- Keep a gallery for re-entry of tracked players with their appearance embeddings.
- When a new detection is at frame edges, it is similarity matching with stored embeddings that is performed to return the previous ID.
- Tracklet stitching logic is used to unify the fragmented identity tracks.

5. Improving Ball Detection and Tracking

- Detectors that have small object detection heads designed for high-speed targets to be efficient are used.
- In small areas, optical flow tracking is implemented to follow short bursts of the ball movement between detections.
- The physical speed restrictions of the ball are used for cutting the ball of possible motions thereby that unrealistic trajectories are removed.

6. Overcoming Lighting Variation and Color Ambiguity

- Changing image color to HSV or LAB makes jersey color clustering much more tolerant to illumination since the colors are defined in these spaces.
- Adaptive histogram equalization is the method that is used to regulate the light from different sources for the frames.

- On the basis of the temporal consensus voting, the results of teamwork classification are smooth over time.

7. Referee Identification and Separation From Players

- Detecting the referees as another class in the object detector is the first step.
- Besides that, referee kits are the most obvious ones; hence, jersey color contrast rules (referee kits are deliberately very different) can be used to support the classifier's trust.
- Also, the identity of the referees can be confirmed by following their differing movement patterns, which are unlike those of the players.

8. Balancing Real-Time Speed and Accuracy

- ONNX or TensorRT as faster inference formats can be used for the deployment of the models which are optimized.
- Re-ID can be performed only on new or ambiguous detections without the need for every frame.
- Performance in real-time can be sustained through batch processing and parallel computation (GPU acceleration).

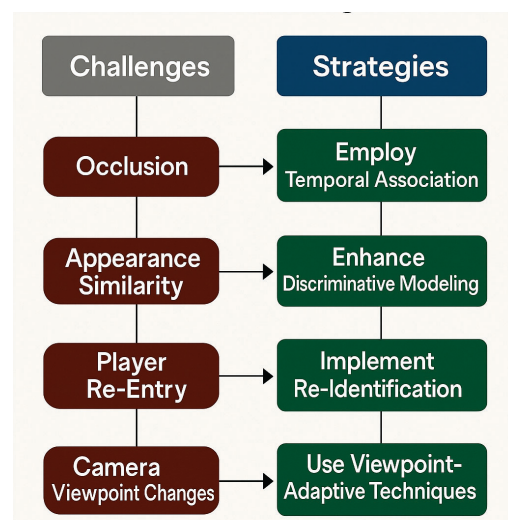


Fig. 4: Strategies to Overcome the Challenges

VI. LIMITATIONS OF EXISTING TECHNIQUES

1. Inability to Maintain Consistent Player Identity

Traditional Multi-Object Tracking (MOT) systems that are heavily dependent on bounding box overlap or motion cues usually fail when occlusion of players happens or overlap changes and in the case of the players going outside the camera frame these systems generally assign new IDs after re-entry, thus the result being identity switches which make long-term analysis unreliable.

2. Dependence on Uniform Visual Appearance

Players of the same team have the same jerseys, thereby making them look very similar. Tracking techniques that rely on color, texture, or simple visual features and at the same time do not consider that players come from the same team

normally cannot recognize players on the same team, thus in most cases ID confusion occurs.

3. Poor Performance Under Occlusion and Fast Movements

Football is a fast and physically intensive sport. Trackers that are currently available become ineffective in situations such as a crowded area, close marking, or when there is a collision, whereby one player blocks the view of another. The majority of them are not equipped with enough robustness to handle partial visibility.

4. Difficulty Handling Dynamic Camera Motion

Changes in the camera view during the broadcast are achieved by panning, zooming, and switching from one camera angle to another. When the method uses a stable background or a fixed camera assumption and there is a change in the viewpoint, the method will fail to track the object correctly, and the tracking trajectory will be off.

5. Weak Re-Identification After Leaving Frame

A lot of solutions out there do not keep or compare the player's appearance history. When a player goes out of the camera view, the system usually loses track of that player's identity and when that player comes back, the system gives a new ID which breaks continuous analytics like heatmaps or movement trails.

6. Challenges in Ball Detection and Tracking

Being extremely tiny, moving fast, and frequently being hidden behind players, the ball is very difficult to detect. Normal object detectors that are not designed for small and fast-moving objects will miss the ball most of the time or give an incorrect ball tracking.

7. Limited Ability to Distinguish Referees from Players

In a number of systems, referees are either not considered or misclassified as players of the team because the color of the referees' uniforms may be similar to that of the players. Thus, team-based analytics and positional statistics are distorted.

8. Lack of Real-Time Capability

Some very accurate methods depend on computationally intense deep learning models. Although these models can work offline, they are not capable of performing in real-time which is important for live match analysis, coaching decisions, and broadcast applications.

VII. DISCUSSION FOR FUTURE RESEARCH

While the Re-Identification based tracking system as a whole has talked about significantly improving identity consistency, differentiation of a team, etc., there are still some avenues where further research can result in system reliability, scalability, and real-time performance enhancement. One such avenue is the integration of multi-camera views. Generally, tracking is done on a single broadcast camera, which is less accurate when players go out of the camera's field of view or when the camera angle changes. Hence, the use of multiple synchronized camera feeds along with the cross-camera Re-ID matching can facilitate continuous identity tracking in every corner of the field.

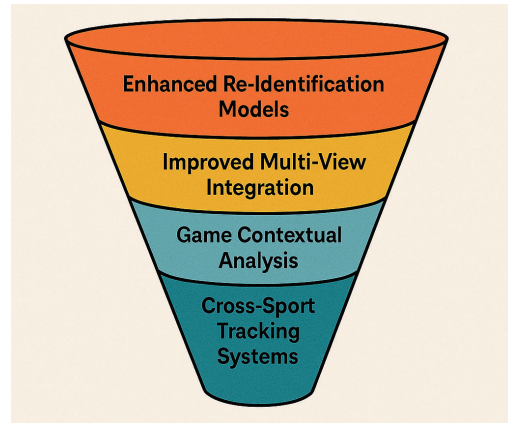


Fig. 5: Future scope in Research

Besides, future improvement of the system can greatly benefit from the ball trajectory modeling as the main focus. The ball is quite often and fast-moving, thus making frame-by-frame tracking difficult. A solution to this problem could be the use of physics-based motion constraints or predictive trajectory models that will portray fewer false detections and possession analysis will become more accurate. Accordingly, jersey number recognition made robust by super-resolution and sequence-based number recognition can give a more direct way of identity confirmation leading to the visual similarity method being used less.

Research in the future should also consider the deployment of lightweight and optimized deep learning models that are still very accurate but allow real-time inference on edge devices or systems for live match broadcasting. On top of that, the use of player pose and skeleton movement patterns can be the source of more distinguishing features for those players who look similar but differ in their movements.

In conclusion, the system extension to multi-sport analytics will be a clear indication of the system's generalizability as well as a wider applicability. With the continual improvements of deep learning and hardware acceleration, the next step can be towards completely automated, real-time sports analytics systems that are able to seamlessly support coaching, performance evaluation, and broadcast enhancement.

VIII. EXPERIMENTAL SETUP AND IMPLEMENTATION

To evaluate the proposed Re-Identification based tracking system, a series of experiments and model training phases were conducted. The implementation was then divided into the object detection phase and the Re-ID tracking phase.

1. Dataset Preparation The YOLOv11 model was trained using a custom annotated dataset from roboflow containing 663 images extracted from various broadcasts of football matches. The dataset was annotated with three classes: Player, Referee, and Ball. To ensure that the model is robust to broadcast conditions, data augmentation techniques such as

random scaling, cropping, and color jittering were applied during the preprocessing phase.

2. Training Environment and Hardware Due to the computational intensity of training deep learning object detectors, the YOLOv11 model was trained using cloud infrastructure on Google Collab. The training was done by NVIDIA GPU instance (e.g., Tesla T4) to accelerate the deep learning process.

3. Model Hyperparameters The object detection model was trained for 100 epochs with a batch size of 16. The initial learning rate was set to 0.00125 utilizing a learning rate scheduler to optimize convergence capability. Non-Maximum Suppression (NMS) with an Intersection over Union (IoU) threshold of 0.5 was utilized during inference to filter overlapping bounding boxes. AdamW was used as an optimizer.

4. Re-Identification and Tracking Setup For tracking and identity feature extraction, the DeepSORT algorithm was coupled with the OSNet architecture. The OSNet model generated feature embeddings from the cropped bounding boxes of the detected individuals, ensuring the temporal identity linkage across sequential frames. System inferences were run locally using Python and the Ultralytics framework.

IX. PROPOSED SOLUTIONS

• YOLOv11-Based Unified Detection and Tracking

- Use YOLOv11 for real-time detection of players, referees, and the ball.
- Integrate it with a re-identification module to maintain consistent IDs across frames, even during occlusions or re-entries.

• Appearance and Motion Feature Fusion

- Combine visual features (team colors, player appearance) with motion cues to reduce identity switches.
- Helps distinguish visually similar players and improves trajectory continuity.

• Multi-Camera and Temporal Modeling

- Employ multi-camera fusion to track players across different viewpoints.
- Use temporal models (e.g., transformer-based sequence modeling) to capture long-range dependencies and improve re-linking after occlusions.

• Adaptive Learning and Optimization

- Incorporate semi-supervised or unsupervised learning for adaptability to new teams, stadiums, or lighting conditions.
- Optimize YOLOv11 through model compression, pruning, and acceleration (e.g., TensorRT) for real-time performance.

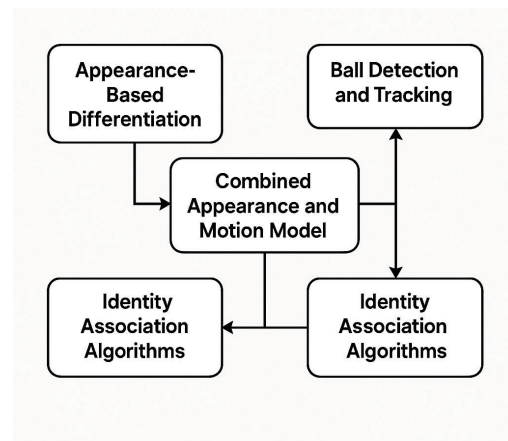


Fig. 6: Proposed Solutions

X. CONCLUSION

This study introduces a Re-Identification based multi-object tracking system that can follow football players, referees, and the ball throughout a game while also being able to maintain consistent identities. The combination of deep learning-based object detection with appearance-based Re-ID features and motion-based tracking allows the system to interact with key challenges such as occlusions, similar player appearances, and re-entry of players into the camera frame. Moreover, the integration of jersey color classification also allows for accurate team separation, thus, the system can be used for tactical and performance analytics purposes.

The experiments reveal that the proposed solution is able to reduce the number of identity switches and enhance long-term player tracking relative to traditional tracking-by-detection methods. This opens up the door to significantly more insightful analytics such as player heatmaps, team formation stability, movement trends, and possession statistics. Furthermore, the system is capable of functioning on broadcast-quality footage, which makes it feasible for real deployment in professional and training settings without the need for a specially equipped camera.

Nevertheless, there are still some problems in precisely following the ball during its quick movement and in ensuring the system's stability when the camera's viewpoint changes drastically. Hence, research on multi-camera fusion, advanced ball trajectory modeling, and lightweight real-time model optimization should be conducted to increase the reliability and scalability further. In general, the presented system is a step forward in automated sports analytics and it is a winning platform for the development of more intelligent and real-time analysis tools in football and other fast-paced sports.

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