**Assignment:** **Soccer Player Re-Identification in Sports Footage – Report**

**Objective**

The goal of this assignment was to implement \*\*player re-identification (Re-ID)\*\* techniques in soccer footage. Two options were addressed:

1. Option 1: Cross-Camera Player Mapping – Match player identities across two different camera feeds (`broadcast.mp4` and `tacticam.mp4`)

2. Option 2: Re-Identification in a Single Feed – Ensure consistent player IDs over time, even when players go out of frame and reappear

Both tasks simulate real-world sports analytics scenarios where maintaining persistent identity is crucial for performance tracking, tactical analysis, and automated commentary.

**Approach and Methodology**

**General Setup**

1)We used a pre-trained YOLOv11 model fine-tuned for soccer player detection and applied built-in tracking algorithms like \*\*BoT-SORT\*\* for ID persistence.

2)To ensure robustness beyond basic tracking, we implemented custom logic using visual features and similarity matching for both tasks.

**Option 1: Cross-Camera Player Mapping**

**Steps:**

1. Run object detection + tracking independently on both videos

2. Extract first appearance crops of each player

3. Use “HSV histogram comparison” and “cosine similarity” to match appearances

4. Save mapping between Broadcast ID and Tacticam ID in JSON format

**Outcome:**

- Successfully matched several players across cameras

- Mappings saved in `cross\_camera\_mapping.json`

- Accuracy limited by lighting differences and pose variation

**Option 2: Re-Identification in a Single Feed**

**Steps:**

1. Run detection and tracking on `15sec\_input\_720p.mp4`

2. Build a “Re-ID memory bank” that stores appearance features of first-seen players

3. When a player reappears after being out of view, compare its features with known ones

4. Assign consistent IDs based on best match

5. Output an annotated video showing persistent IDs

**Outcome:**

- Consistent IDs maintained even after temporary disappearance

- Annotated output video saved as `output\_reid\_video.mp4`

- Simple but effective logic using color histograms

**Techniques Tried and Outcomes**

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| --- | --- | --- |
| Technique | Description | Outcome |
| YOLOv11 + BoT- SORT Tracker | Used for initial detection and tracking | Provided good baseline ID assignment and motion tracking |
| Color Histogram Matching | HSV histogram of player crops used for visual similarity | Worked well under similar lighting; failed with large viewpoint change |
| Cosine Similarity | Measured similarity between feature vectors | Improved matching accuracy over raw histogram comparison |
| Custom Re-ID Memory Bank| | Stored and compared player appearances | Enabled robust re-identification beyond tracker limits |

**Challenges Encountered**

1. \*\*Lighting Variation\*\*

- Players appeared differently in various frames or camera angles

- Affected histogram-based matching accuracy

2. \*\*Pose and Viewpoint Changes\*\*

- Players seen from different angles looked visually different

- Caused mismatches in cross-camera mapping

3. \*\*Occlusions and Fast Movement\*\*

- Trackers sometimes lost players during heavy occlusion

- Led to ID switches or new ID assignments on reappearance

4. \*\*Model Limitations\*\*

- The provided `best.pt` model was basic and not trained on diverse soccer data

- Missed some players or generated false positives in complex scenes

What Remains / How to Proceed with More Time/Resources

While both options were successfully implemented, there are several improvements that could be made:

1. \*\*Use Deep Feature Embeddings\*\*

- Replace histogram-based matching with deep Re-ID models like \*\*OSNet\*\*, \*\*FastReID\*\*, or \*\*StrongSORT\*\*

- These models learn robust features invariant to pose, lighting, and scale changes

2. \*\*Add Spatial Consistency Checks\*\*

- For cross-camera mapping, use field alignment or spatial priors to improve matching

- Map player positions onto a common coordinate system (e.g., top-down pitch map)

3. \*\*Improve Long-Term Tracking\*\*

- Add trajectory prediction to handle long-term occlusion

- Integrate Kalman Filters or LSTM-based motion models

4. \*\*Optimize for Real-Time Performance\*\*

- Reduce inference latency using TensorRT or ONNX optimizations

- Enable live feed processing and real-time visualization

5. \*\*Enhance Model Accuracy\*\*

- Fine-tune the YOLO model on additional soccer datasets

- Improve detection accuracy and reduce false negatives

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**Final Summary**

This submission demonstrates functional implementations of \*\*both options\*\* of the assignment:

🡪 Cross-camera player mapping- with visual matching

🡪 Persistent ID assignment- in a single feed with Re-ID logic