📄 Cross-Camera Player Mapping: Brief Report

🧠 Objective

The goal of this project is to **automatically identify and map players** between two video streams:

- 🎥 A **broadcast camera** (side view)
- 🛰️ A **tacticam camera** (top view)

This helps in combining tactical insights with live broadcast footage by linking the same players across camera perspectives.

⚙️ Approach & Methodology

Our approach combines **detection, tracking, appearance matching**, and **spatial transformation**:

1. **Detection**:
   - Used a custom-trained **YOLOv8 model (best.pt)** fine-tuned to detect players and the ball.
2. **Tracking**:
   - Applied **DeepSORT** to track player movement across frames and assign consistent IDs.
3. **Re-Identification (Re-ID)**:
   - Used **OSNet** from TorchReID to extract appearance embeddings per track.
   - Augmented with **HSV color histograms** (jersey colors) for improved robustness.
4. **Homography Estimation**:
   - Automatically matched player centroids across both views using ID consistency and computed the homography matrix using **RANSAC**.
5. **Multi-Modal Matching**:
   - Combined **appearance similarity** and **projected spatial distance** (via homography).
   - Tuned appearance weight dynamically to balance both cues.
6. **Evaluation & Visualization**:

- Generated annotated videos with mapped IDs and confidences.
- Calculated **Euclidean distances** between mapped player centers.
- Produced a JSON report with **mean, std, max errors**, and worst cases.
- Optional: Visual plot of match confidence and distance.

🔬 Techniques Tried & Their Outcomes

Technique	Outcome
Manual 4-point homography	❌ Error-prone, subjective, and frame-dependent
Automatic centroid-based homography	✅ More accurate, frame-consistent, and adaptable
OSNet Re-ID only (appearance)	⚠️ Worked, but failed when jerseys looked similar
Combined Re-ID + position matching	✅ High accuracy, adaptable across player occlusions and viewpoints
Color histogram (jersey crops)	✅ Improved Re-ID where visual features failed

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⚠️ Challenges Encountered

- **Manual Point Selection**:
  - Selecting 4 homography points per video was inaccurate and inconsistent.
- **Camera Angle & Perspective Mismatch**:
  - Top-view vs side-view introduces severe distortions making spatial matching non-trivial.
- **Player Occlusion**:
  - In broadcast footage, players often occlude each other, degrading detection/tracking.
- **Small Dataset for Fine-Tuning**:
  - Custom YOLO model was trained on a limited dataset, leading to minor misdetections.

⏳ What Remains / Future Work

This system is functional and demonstrates robust player mapping. However, given more time or resources:

1. **Improved Homography Refinement**:
   - Iteratively update homography using matched player positions over many frames.
2. **Ground-Truth Evaluation**:
   - Integrate manual GT labels for precision, recall, and F1-score analysis.
3. **Ball Tracking**:
   - Extend to multi-camera ball trajectory tracking with re-ID and physics priors.
4. **Web-Based Dashboard**:
   - Live sync and visualizations using Streamlit or Dash for real-time analysis.
5. **Generalization**:
   - Test and adapt to new datasets and stadiums with different camera placements.