Project Report: Real-Time Soccer Player Re-identification and Tracking

1. My Approach and Methodology

In this project, my objective was to detect, track, and re-identify soccer players from a 15-second video using a pre-trained YOLOv11 model. The main challenge was ensuring that each player retained the same identity even after exiting and re-entering the frame. I addressed this by combining YOLOv11 for object detection with Deep SORT for tracking, augmented by TorchreID-based visual re-identification. My final solution simulates real-time player tracking with high visual consistency.

2. Techniques I Tried and Their Outcomes

- **Color Histogram Embeddings (Technique 1):**

Initially, I attempted to use color histograms to represent visual appearance features. This approach performed poorly due to the uniformity of team jerseys, lighting variations, and occlusions, and failed to maintain consistent identities.

- **Deep SORT with MobileNet Embedder (Technique 2):**

Next, I integrated Deep SORT with its default MobileNet embedder, without TorchreID, since TorchreID wasn't functioning at the time. While this improved over the histogram approach, it still lacked robustness. The tracker struggled with re-identification when players exited and re-entered the frame.

- **Deep SORT with TorchreID (Technique 3 – Final Choice):**

After successfully getting TorchreID to work, I evaluated multiple pretrained models. I found that osnet_ain_x1_0 provided the best results. It delivered strong identity preservation across challenging frames. This became the backbone of my tracking pipeline.

3. Challenges I Faced

- **Finding a Re-identification Strategy:**

Initially, I had to brainstorm an effective re-ID solution. Since I already had a trained YOLOv11 model, I focused on identifying a tracking system that would complement it. Deep SORT proved to be the best fit.

- **Integrating TorchreID:**

Getting TorchreID to work with Deep SORT required careful setup and troubleshooting. Once I resolved dependency issues, it opened the door to much better tracking performance.

- **Choosing the Best Embedder:**

TorchreID offered many models. I experimented with several and selected osnet_ain_x1_0, which outperformed the rest in terms of re-ID accuracy and speed.

- **Filtering Detections and Parameter Tuning:**

I filtered out low-confidence detections and very small boxes to avoid noisy tracking. I also fine-tuned Deep SORT parameters like max_age, n_init, nms_max_overlap, max_iou_distance, max_cosine_distance, and nn_budget. These adjustments had a major effect on tracking stability and identity preservation.

4. Remaining Issues and Next Steps

Despite my best efforts to explore and implement various techniques for player re-identification, the results remained limited. In most cases, only 1–2 players were successfully re-identified after leaving and re-entering the frame, while others were assigned new track IDs. I thoroughly researched and tested multiple strategies, including Deep SORT parameter tuning and evaluating different TorchreID models, but consistent re-identification proved to be a complex challenge.

If I had more time and resources, I would focus on:

- Designing a customized re-ID model trained specifically on soccer match data to improve embedding quality.
- Enhancing temporal consistency through trajectory-based heuristics to recover lost identities.
- Incorporating auxiliary cues like jersey numbers or color clustering for ID correction.
- Experimenting with memory-enhanced tracking mechanisms that store visual features over longer temporal windows.