Player Re-Identification in Sports Footage

Technical Report

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1. Objective

The primary goal of this project was to develop a robust system for real-time player re-identification in sports footage. The system needed to meet several critical requirements:

- **Consistent ID Assignment**: Maintain stable player identities across video frames
- **Re-entry Recognition**: Reassign the same ID when players re-enter the scene after leaving
- **Real-time Processing**: Simulate real-time performance suitable for live sports applications
- **Runtime Efficiency**: Balance accuracy with computational performance

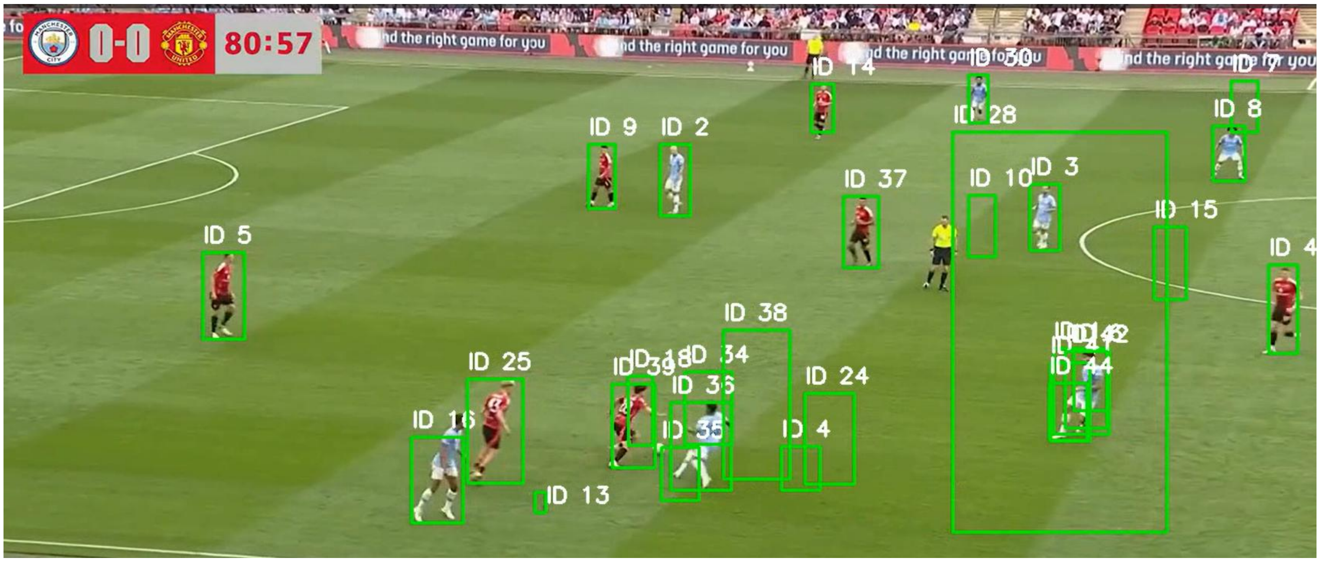
The challenge was to create a system that could handle the dynamic nature of sports environments, where players frequently move in and out of frame, experience occlusions, and undergo appearance changes due to lighting and movement.

2. Approach & Methodology

2.1 Initial Implementation: YOLOv8 + DeepSORT

Our initial approach utilized the established combination of YOLOv8 for player detection and DeepSORT for tracking and re-identification. While this baseline setup provided quick implementation, several limitations became apparent:

- **Inconsistent ID Maintenance**: DeepSORT frequently failed to maintain consistent player IDs, particularly during scene re-entry
- **Weak Appearance Matching**: The appearance-based matching component proved unreliable in dynamic sports environments
- **Limited Re-identification Capability**: Poor performance when players left and returned to the field of view

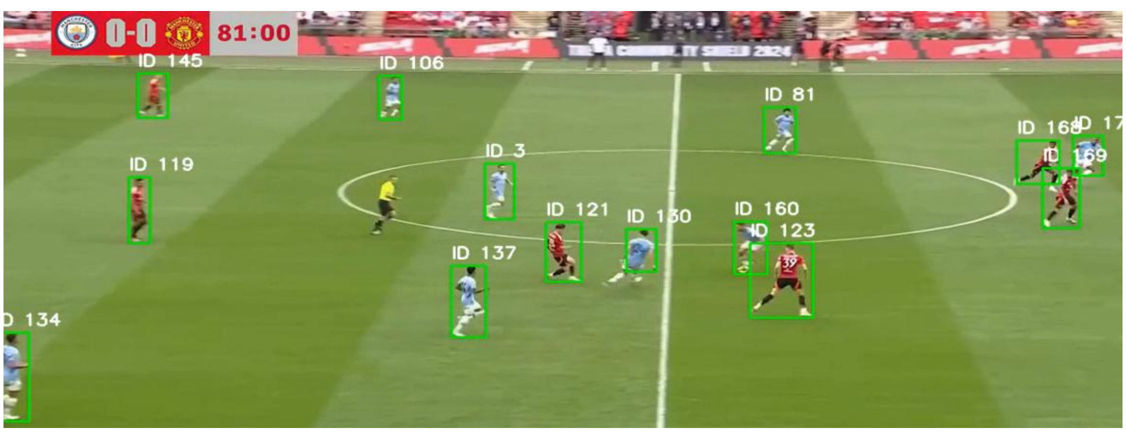


As you can see in the image it's inconsistent

2.2 Transition to OC-SORT

Recognizing the limitations of DeepSORT, we transitioned to OC-SORT (Observation-Centric SORT), a more recent and lightweight tracking algorithm. OC-SORT offered several advantages:

- **Improved Temporal Association**: Better motion estimation through enhanced IOU-based matching
- **Kalman Filter Integration**: More robust motion prediction capabilities
- **Computational Efficiency**: Lighter weight compared to DeepSORT

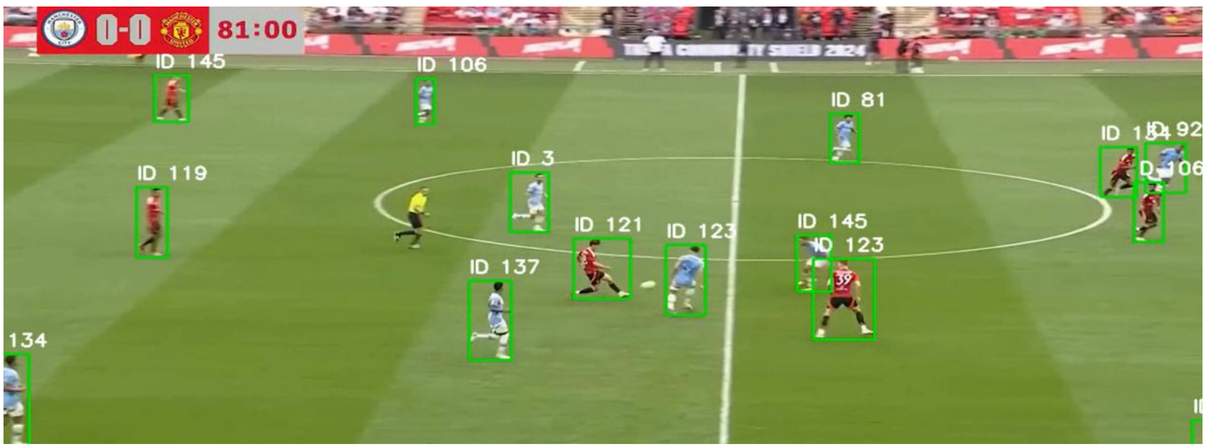


However, OC-SORT alone lacked appearance-based features, meaning ID consistency still failed when players exited the frame. As you can see in the image.

2.3 Appearance-Based Re-Identification Integration

To address the limitations of motion-only tracking, we integrated appearance-based re-identification using ResNet50:

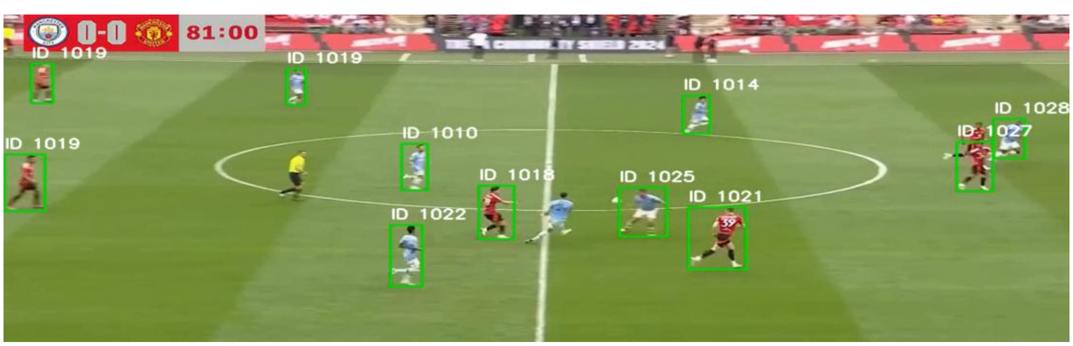
- **Feature Extraction**: ResNet50 backbone extracted appearance embeddings from cropped player images
- **Embedding Storage**: Created a comprehensive embedding database for each detected player
- **Similarity Matching**: Implemented cosine similarity comparison for identity verification



2.4 Gallery-Based Re-Identification System

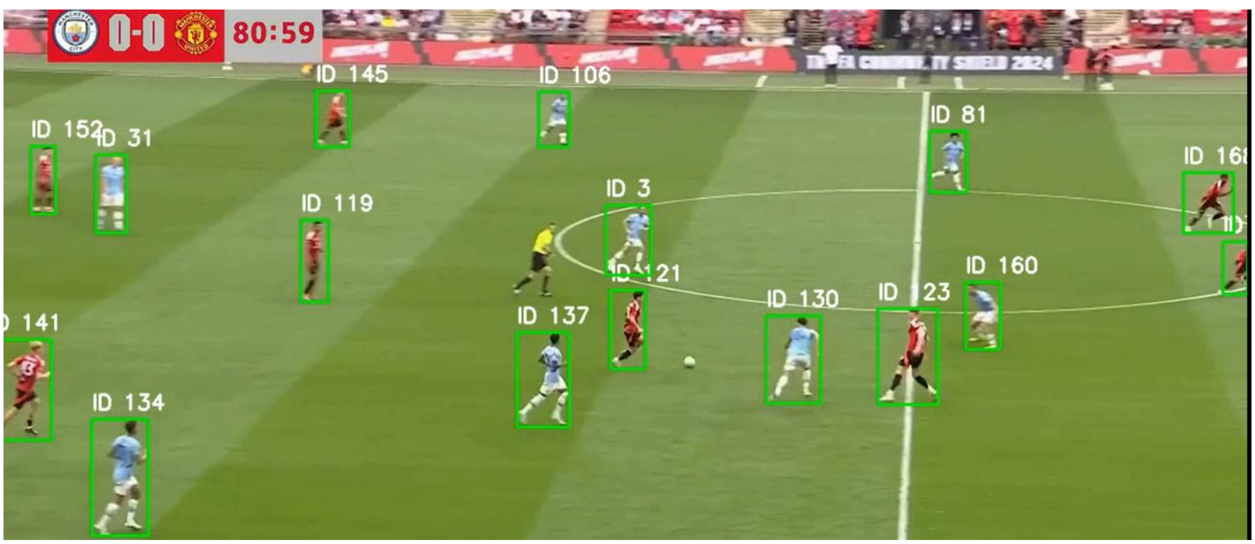
The core innovation was implementing an id_gallery system:

- **Embedding Storage**: Maintained appearance embeddings for each assigned player ID
- **Similarity Threshold**: Used cosine similarity > 0.7 for positive ID matches
- **New Player Handling**: Assigned new IDs for players without gallery matches
- **Persistence Logic**: Enabled consistent ID assignment across re-entries



3. Techniques Tried & Outcomes

Technique	Implementation	Outcome
YOLOv8 + DeepSORT	Baseline tracking system	Fast processing but inconsistent ID maintenance
OC-SORT Integration	Motion-based tracking upgrade	Improved tracking stability, lacked re-ID support
Tracklet-Based Gallery Update	Stored embeddings after N=5 frame persistence	Stabilized ID assignment process
Gallery Averaging	Averaged multiple embeddings per ID	Enhanced re-ID matching stability
Temporal Smoothing	Smoothed embedding matches using confidence + history	Improved frame-to-frame consistency
Combined System	All techniques integrated	Overall improvement with occasional mismatches during long occlusions



The final the output using all three techniques.

4. Challenges Encountered

4.1 Embedding Quality Issues

Problem: ResNet50 struggled with small or partially occluded players, leading to poor embedding quality.
Impact: Reduced re-identification accuracy, especially for distant players or during crowd scenes.

4.2 ID Switching on Re-entry

Problem: Players sometimes received new IDs despite embedding matching due to appearance changes.
Impact: Inconsistent identity maintenance, particularly after lighting changes or pose variations.

4.3 Kalman Filter Limitations

Problem: Long-term motion predictions failed without consistent detections, causing tracking drift.
Impact: Lost tracks during extended occlusions or rapid movement changes.

4.4 System Integration Complexity

Problem: Integrating appearance information into the existing motion-only OC-SORT tracker required significant modifications to internal data structures and association logic.
Impact: Increased debugging complexity and potential for tensor shape mismatches.

5. Next Steps (If More Time Available)

5.1 Advanced Re-Identification Models

- **OSNet Integration**: Implement OSNet (Omni-Scale Network) for more robust appearance features
- **TransReID**: Explore transformer-based re-identification models for better long-term associations
- **FastReID**: Utilize state-of-the-art fast re-identification frameworks

5.2 Domain-Specific Model Training

- **Sports-Specific Fine-tuning**: Fine-tune ResNet50 on sports player datasets rather than relying on ImageNet pre-training
- **Custom Architecture**: Develop sport-specific embedding networks trained on player appearance data

- **Multi-Sport Adaptation**: Create models that can adapt to different sports environments

5.3 Enhanced Tracking Robustness

- **Improved Occlusion Handling**: Develop better strategies for maintaining identity during full occlusions
- **Temporal Voting Systems**: Implement tracklet-based ID voting for more robust re-identification decisions
- **Multi-Modal Fusion**: Combine appearance, motion, and contextual information for better tracking

5.4 Performance Optimization

- **Real-time Optimization**: Optimize inference speed for true real-time performance
- **Edge Deployment**: Adapt the system for edge computing environments
- **Batch Processing**: Implement efficient batch processing for multiple simultaneous tracks

6. Remaining Limitations & Future Work

Despite meaningful progress, the system still has several limitations. The most significant issue is the inconsistency in re-identifying players who re-enter the frame after exiting — they are often assigned new IDs even with gallery-based appearance matching. Additionally, when players move quickly or overlap heavily, the tracker struggles to maintain stable identities, leading to frequent ID switches. Although gallery averaging of embeddings helped improve re-ID consistency to some extent, it also introduced false matches, causing multiple distinct players to share the same ID. A more advanced appearance model (e.g., OSNet or a fine-tuned ReID model) and smarter temporal ID voting could significantly improve reliability. With more time, training on domain-specific data and integrating temporal + appearance fusion would be the next steps toward a production-ready system.

7. Conclusion

This project provided valuable insights into the complexities of real-time player re-identification in sports footage. While the final system demonstrates functional capability, it also highlights the challenging nature of maintaining consistent identity across dynamic sports environments.

Key Learnings:

- **Multi-Modal Approach**: The combination of motion and appearance features proved more effective than either approach alone
- **System Integration**: Significant engineering effort is required to integrate different tracking paradigms effectively
- **Real-World Complexity**: Sports environments present unique challenges that require specialized solutions beyond standard computer vision techniques

Technical Growth:

Through this project, I gained hands-on experience with:

- Advanced object detection and tracking systems
- Deep learning model integration and optimization
- Real-time computer vision pipeline development
- Problem-solving in dynamic, challenging environments

Future Enthusiasm:

This project has deepened my interest in computer vision applications, particularly in sports analytics and real-time systems. The challenges encountered have motivated me to continue exploring more sophisticated approaches to player tracking and re-identification.

I am excited about the possibility of continuing this work and contributing to innovative computer vision solutions at Liat.ai. The combination of technical challenges and practical applications in sports technology represents exactly the kind of work I am passionate about pursuing.

Thank you for this opportunity to demonstrate my technical capabilities and problem-solving approach. I look forward to discussing this work further and potentially contributing to the innovative projects at Liat.ai.