② Player Re-Identification in Sports Footage

This project implements a real-time football analytics pipeline using deep learning and computer vision. It integrates **YOLOv8** for object detection, **SORT** for tracking, **CLIP** for team classification and re-identification, and provides basic analytics such as **speed**, **distance**, and **ball possession stats**.

■ Repository Contents

```
models/
yolo_players.pt  # YOLO model trained for players & ball
sort/
sort.py  # SORT tracker
videos/
15sec_input_720p.mp4  # Match video input
results/
final_stats_overlay.mp4# Output video with analytics
vlm_action_tracking.py  # Main pipeline script
Player Re.docx  # This report
```

O Setup Instructions

Requirements

- Python 3.8+
- GPU Recommended for CLIP & real-time performance

E Install Dependencies

```
pip install torch torchvision opencv-python numpy pillow scikit-learn
pip install git+https://github.com/openai/CLIP.git
pip install ultralytics
```

Ensure the YOLOv8 model is placed at:

```
models/yolo players.pt
```

► Run the Project

python vlm action tracking.py

This processes the video and displays:

- Player tracking with persistent IDs
- Team classification via jersey color
- Speed & distance traveled
- Ball tracking with possession stats

Project Objective

Detect, track, and analyze players and the ball from football footage using:

- **Re-identification** (ID persistence even after occlusion)
- Team classification (jersey-based using CLIP)
- Player analytics (speed, distance)
- Ball control percentages

Q What I Did

1. Player & Ball Detection

- YOLOv8 model trained on player and ball classes
- Filters detections by confidence and class

2. Tracking & Re-Identification

- Uses **SORT** for short-term tracking
- Adds **CLIP-based re-identification** to retain consistent player IDs
- Jersey crop passed to CLIP for embedding & cosine similarity check

3. Team Classification

- Jersey region extracted (top 50% of bbox)
- CLIP compares crop to prompts like:
 - o "a football player wearing a red Manchester United jersey"
 - o "a football player wearing a blue Manchester City jersey"
- Softmax + argmax to assign class (Team Red, Team Blue, Referee)

4. Player Analytics

- Speed calculated using pixel distance per frame (converted to km/h)
- Distance summed over time
- Ball possession calculated based on proximity to player centers

∀ What Worked & What Didn't

Method	Description	Result
YOLOv8	Player/ball detection	✓ Robust & accurate
SORT	Short-term tracking	✓ Works well for most cases
CLIP + Re-ID	Jersey embedding re-identification	✓ IDs persist after occlusion
CLIP + Prompt	Natural language-based team classification	
Speed Metric	Distance per frame (0.05m per pixel approx)	✓ Informative but needs real calibration
Ball Control	Proximity-based possession estimate	

▲ Problems Faced

- CLIP slow on CPU → switched to GPU
- ID switch with long occlusion in SORT → fixed with embedding comparison
- Jerseys not always visible → classification less reliable
- No pixel-to-meter calibration → speed/distance estimates are relative
- Ball tracking misses mid-air shots (if not detected as "ball")

F Future Improvements

- Add robust action recognition (e.g. with R3D, SlowFast)
- Add OCR for jersey number or face recognition for player identity
- Integrate play pattern recognition (passes, tackles, goals)
- In Better speed calibration using field dimensions or homography
- Add commentary or play-by-play generation

♣ My Experience

This project helped me combine vision-language models like CLIP with traditional computer vision. I learned how to:

- Use CLIP for classification tasks beyond zero-shot
- Implement tracking + re-ID pipelines
- Apply speed and movement metrics in sports
- Handle edge cases like missing jerseys or occlusions

Contact

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