Player Re-Identification in Sports Footage – Project Report

1. Project Overview

Implementing a reliable player detection, tracking, and re-identification pipeline with a single static sports video feed is the main objective of this project. The system makes use of Deep SORT for multi-object tracking and YOLOv11 for object detection to guarantee consistent identity assignment across frames. Important improvements have been made to increase interpretability and usefulness, including custodian identification, a scaled mini-map visualisation, and a real-time player count overlay.

2. Technical Stack & Frameworks

- The core language for implementation is Python 3.8+.
- Real-time object detection using YOLOv11 (Ultralytics)
- Deep SORT—Multi-object tracking and re-identification based on appearance
- OpenCV: Video input/output, visualisation, and frame processing
- NumPy: Spatial coordinate mapping and array operations
- Virtual Environment: A separate, reproducible Python environment

3. System Design & Methodology

3.1 Preprocessing

A high-resolution input .mp4 video is loaded frame-by-frame.
To remove false positives, detected bounding boxes from YOLO are filtered according to minimum box dimensions and confidence score threshold (e.g., ball, shadows).

3.2 Detection & Re-Identification Pipeline

YOLOv11 is used to detect all visible players with class "person".
Deep SORT is initialized with tuned hyperparameters:

- max_age=20: Maximum number of frames to keep lost tracks.
- n_init=3: Minimum detections before confirming a new object.
- max_cosine_distance=0.35: Appearance similarity threshold for identity matching.

The combination ensures temporal consistency of IDs and smooth re-identification under short occlusions and motion blur.

3.3 Post-Processing & Visualization

Each player is surrounded by bounding boxes with bold ID labels and white outlines.
A designated GOALKEEPER_ID is visually distinguished using a red bounding box and mini-map marker, after manual inspection.
A mini-map overlay is rendered on the bottom-right of the frame, showing scaled player positions over a synthetic football pitch.
A real-time player count is displayed to indicate active tracking.

4. **Techniques Explored & Empirical Outcomes**

TECHNIQUE	OUTCOME
Yolov11 + Deep SORT	High frame-rate performance; ~real-time tracking with consistent identities
Cosine distance tuning	Reduced id-switching frequency; better appearance matching under occlusion
Box size and aspect ratio filtering	Eliminated most false positives (ball, crowd edges, shadows)
Manual goalkeeper id marking	Simple but effective; ensured role-specific visualization
Trajectory drawing (rejected)	Overly cluttered in dense scenes; removed in final version
Jersey colour clustering (rejected)	Unreliable due to shadows, blur, and similarity in tones
Mini-map overlay	Highly effective; improves spatial awareness and tactical interpretation

5. **Challenges Encountered**

- ID Switching: Players occasionally switched IDs during wide-angle shots or overlapping movement.
  > *Mitigated by adjusting tracker parameters and refining detection filters.*
- Goalkeeper Identification: Dynamic detection of goalkeeper was unreliable due to pose similarity.
  > *Resolved by manually identifying and locking the goalkeeper's ID.*
- Colour-Based Classification: Shadows and broadcast lighting caused jersey colour ambiguity.
  > *Abandoned due to inconsistency; focus shifted to ID and spatial overlays.*
- Overlay Design Trade-offs: Excessive visualization (e.g., trajectories, jersey colour boxes) reduced readability.
  >*Prioritized clarity by selecting only essential overlays***.**

6. **Enhancements Implemented**

1) Goalkeeper Highlighting — Red bounding box + red dot on minimap

2) Mini-Map Rendering — Virtual pitch scaled from player positions
3) Player Count Overlay — Updated per frame
4) False Detection Filtering — Based on aspect ratio, confidence, size
5) Optimized ID Stability — Through tracker tuning and smarter detection filtering

7. Opportunities for Further Development

If extended into a full-scale product or research prototype, the following enhancements can be considered:
If extended into a full-scale product or research prototype, the following enhancements can be considered:

a. Automatic Role Detection
Use pose estimation models or temporal behavioral analysis to infer positions (e.g., keeper, striker, defender).

b. Team Segmentation via Jersey Clustering
Apply K-means or DBSCAN on HSV color histograms from upper-body patches to classify teams.

c. Heatmaps and Spatial Analytics
Generate player heatmaps, zonal occupancy, and density distribution maps over full matches.

d. Ball Detection and Pass Inference
Track the ball separately and infer player-to-player pass sequences.

e. Multi-View Synchronization
Combine feeds from multiple camera angles using homography for better ID preservation and 3D positioning.

f. Web Dashboard Deployment
Use Streamlit or Flask to serve real-time analytics and video overlays via a browser.

8. Conclusion

This project demonstrates a modular and scalable approach to player re-identification using deep learning-based detection and appearance-based tracking. Despite working with a single video feed and limited ground truth, the pipeline achieves a high level of identity consistency and visual interpretability.

By incorporating thoughtful enhancements like minimaps and role-specific overlays, the system not only meets functional objectives but also provides valuable tactical insights — laying a strong foundation for future research or deployment in sports analytics.