Player Re-identification in One Feed
(Report)

1) My final approach

Objective: Detect, assign unique IDs, and track players in video feeds.

- **Key Libraries**: Uses `cv2` (OpenCV) for video/image processing, `numpy` for numerical operations, `csv` for data logging, and `ultralytics` (YOLO) for object detection.
- **System Architecture**: Sequential pipeline involving video input, frame sampling, YOLO-based object detection, feature extraction, custom player tracking/re-identification, data logging, visual output, video output, and track management.
- **Object Detection**: Employs a YOLO model (`best.pt`) to identify player bounding boxes in each frame.
- **Tracking Methodology**: A custom algorithm maintains a `track_db` (tracking database) for active players.
  - **Features Used**: Centroid coordinates (spatial location), dominant jersey color (hue), and bounding box height.
  - **Matching Logic**: New detections are matched to existing tracks based on spatial proximity (`min_dist`), color similarity (`color_thresh`), and height similarity (`height_thresh`). If no match, a new ID is assigned.
  - **Track Management**: Disappeared players are removed from `track_db` after a set period (e.g., 2 seconds) to handle temporary occlusions.
- **Outputs**: Generates an annotated video (`player_tracking_output.avi`) with visual tracking (circles and IDs) and a CSV file (`player_tracking_output.csv`) containing frame-wise tracking data (frame, ID, cx, cy, height, jersey_color).

Techniques I tried and their outcomes:

1) In this technique :

- **YOLOv8 Detection** – Detects players (class 2) in each frame.
- **IoU(Intersection over Union) Filtering** – Removes overlapping detections using IoU > 0.7.
- **DeepSORT Tracker (Standard Built-In Algorithm)** – Tracks players using Kalman filter and Re-ID features.
- **Smooth Bounding Boxes** – Uses Kalman-predicted boxes for stable tracking.
- **CSV Logging** – Saves tracked player IDs and positions frame-by-frame.

Output:

Pros**:**

Accurate Detection, Smooth Tracking, ID Persistence, Simple Integration, CSV Logging

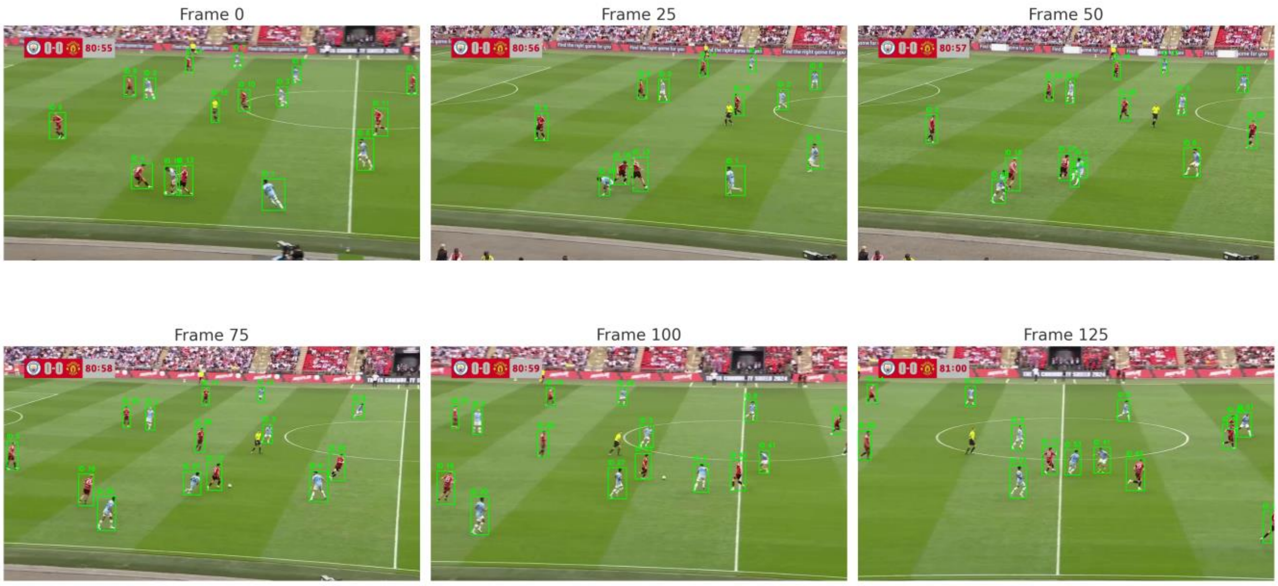
Cons:

ID Switching, Over-filtering

2) In this technique :

- **YOLOv8 Detection** – Detects players (class 2) with confidence > 0.7.
- **ByteTrack Tracker** – Tracks players using IoU-based matching (no Re-ID).
- **Built-in Tracking Pipeline** – Uses `model.track()` with `persist=True`.
- **Custom Tracker Config** – Tweaked using `bytetrack_custom.yaml` for better performance.
- **CSV Logging** – Logs player positions once per second.

Output: 25 frames per second && below data taken at the 1 sec interval:



Pros:

- **Fast & lightweight** – Runs in real-time using YOLOv8 + ByteTrack.
- **No external tracker needed** – Uses built-in `model.track()` API.
- **Good ID consistency** – Works well when players are spaced apart.
- **Customizable tracking** – Configurable via `.yaml` file.
- **Simple logging** – Easy to log data once per second.

Cons:

- **Frequent ID switching** – Happens when players are close or occluded.

- **No appearance-based Re-ID** – Tracker can't remember players visually.

3) In this technique:

- **YOLOv8 Detection** – Detects only players (class 2) with confidence > 0.7.
- **BoT-SORT Tracker(standard built in tracking algorithm)** – Uses improved tracking with motion + appearance features.
- **Custom ID Mapping** – Replaces track IDs with your own consistent `Player_ID`s.
- **Disappearance/Reappearance Logic** – Tracks status (`disappeared` / `reappeared`) manually.
- **Detailed CSV Logging** – Saves ID, position, and player status once per second.

Output :

pros:

- Player Re-identification: System re-identifies players across frames.
- Precise Bounding Boxes: Provides accurate X, Y, Width, Height data.
- Granular Frame Data: Detailed info available for each frame.
- Multi-Player Tracking: Tracks multiple players simultaneously.

Cons:

- Short Tracking Durations: Many players tracked for only a few frames.
- Frequent Appearance/Disappearance: High player ID turnover suggests tracking issues.
- Limited Status Info: Only 'reappeared' status, lacks detail on tracking state.
- No Tracking Loss Info: Doesn't show when players are lost or gaps occur.
- Potential ID Switches: Reappeared' status might not always be correct re-identification.

4) Techniques Used:

- **YOLOv8:** Player detection.
- **Ultralytics Tracking:** Built-in multi-object tracking.
- **Kalman Filter:** Bounding box smoothing.
- **Rule-Based Filters:** Speed, field bounds, and basic color-based team classification.

Pros:

- **Accurate Detection:** Good at finding players.
- **Smooth Movement:** Kalman filter helps with fluid tracks.
- **Team ID:** Basic team classification.
- **Clear Visuals:** Bounding boxes and IDs are well-displayed.

Cons:

- R**edundant Smoothing:** Kalman filter might be unnecessary with built-in tracker.
- **Basic Team ID:** Color-based classification can be unreliable.

•**Hardcoded Settings:** Requires manual tuning for different videos.

5) Techniques Used:

1. **YOLO (You Only Look Once):** For fast object detection (identifying players).
2. **DeepSORT:** For robust object tracking (maintaining player IDs).

Key Pros (Combined System):

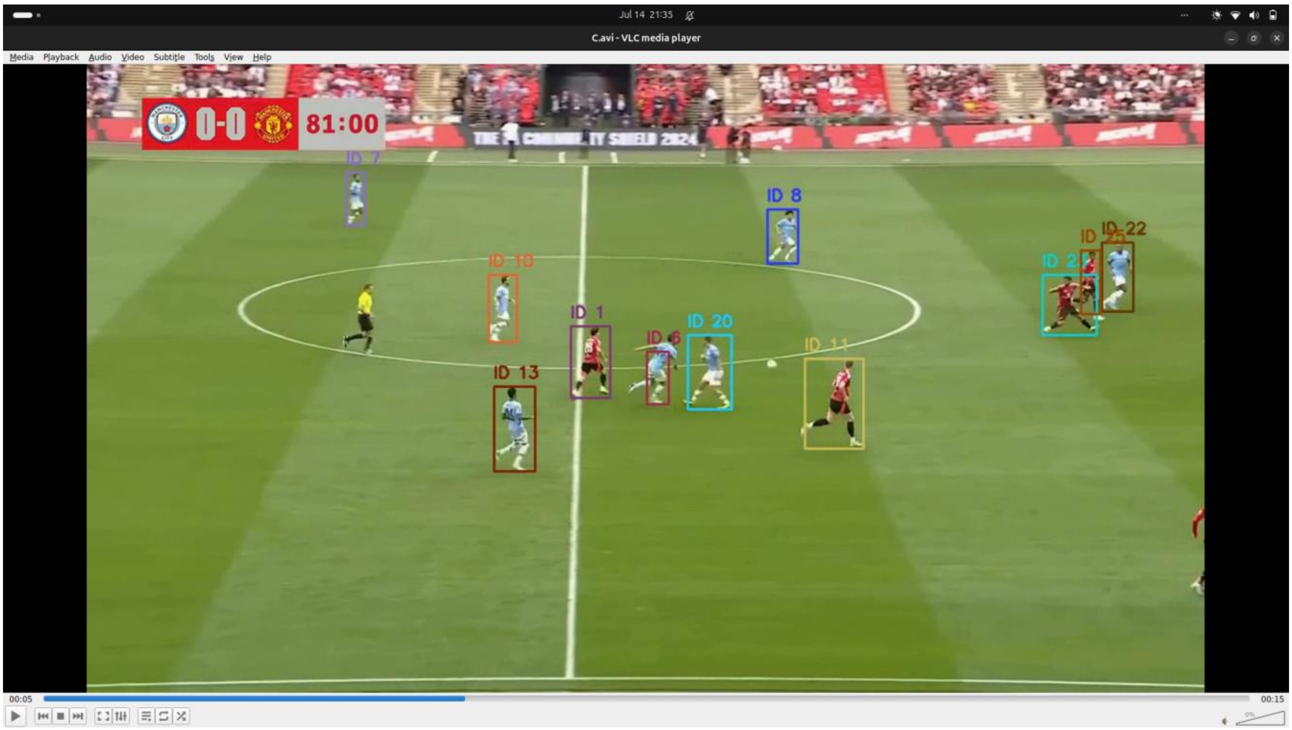
1. **Real-time Performance:** Fast detection and tracking suitable for live video.
2. **Accurate Tracking:** Maintains consistent player identities even with occlusions.
3. **Versatility:** Applicable to various video analysis tasks.

Key Cons (Combined System):

1. **Cumulative Errors:** Detector errors can negatively impact tracking.
2. **Computational Demands:** Requires powerful hardware for optimal performance.

6) **Techniques Used**

1. **YOLOv8 for Detection Only** – Tracking is not handled by a tracker but manually using centroids.
2. **Centroid-Based Matching** – IDs assigned based on Euclidean distance between current and previous detections.
3. **Custom ID Management** – Each new unmatched detection gets a new unique Player ID.
4. **Re-ID Handling via Last Seen Frames** – Players are removed if not seen for `2 seconds` (based on `fps`).
5. **Random Color per ID** – Each player gets a unique random color for better visualization.



Pros

1. **Stable IDs** in moderately crowded scenes with consistent player movement.
2. **Simple to implement** and customize (no deep feature extractor or third-party tracker required).
3. **Good control** over ID assignment and removal via centroid and frame-based logic.
4. **Lightweight solution** – works well on CPU with fewer dependencies.
5. **Scene change handling** – skips frames with >30 detections to avoid audience or noise.

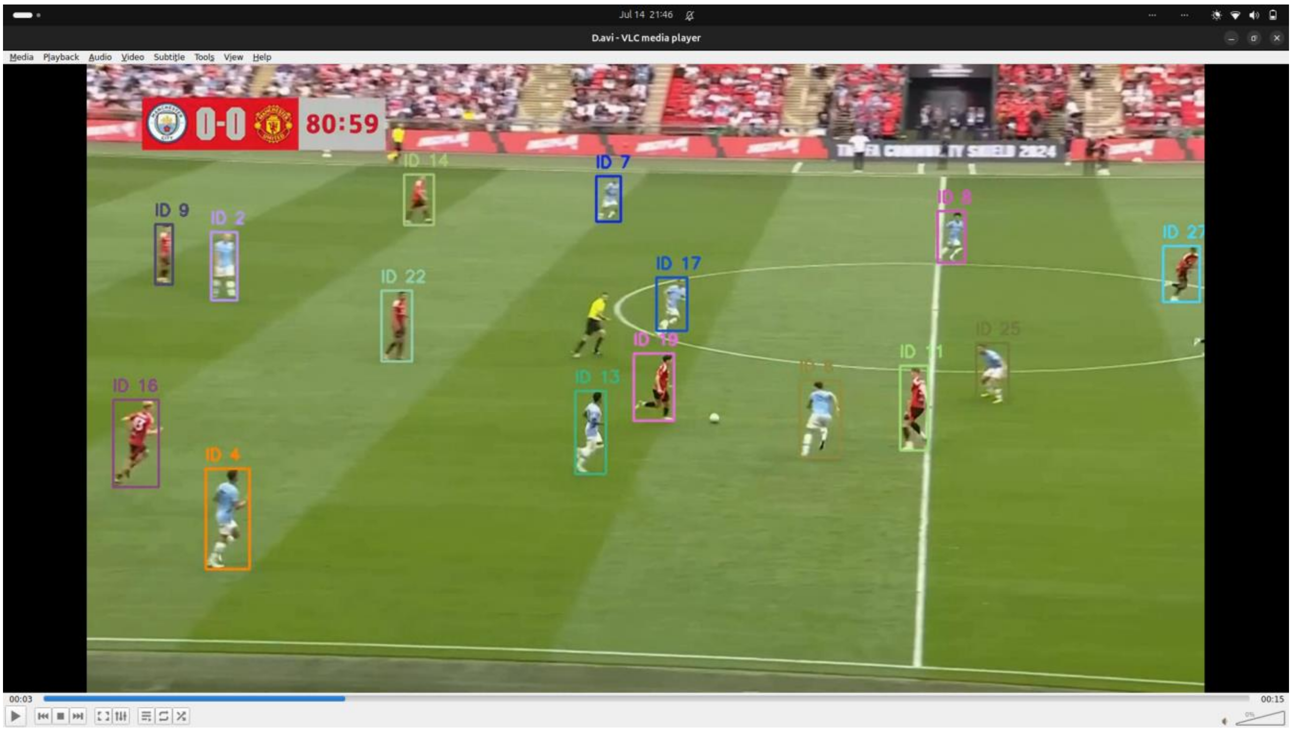
Cons

1. **Fails when players come close** – ID switching or duplication occurs in congested areas.
2. **No appearance matching** – color or jersey pattern isn't considered, only location.
3. **New ID every time player reappears after 2s** – poor long-term ID consistency.
4. **Not robust to occlusion or fast motion** – IDs break if players suddenly change direction.
5. **Manual tuning required** – threshold distance, disappearance time, and frame-skipping need careful tuning.

7)

Technique Used:

I am using a **custom YOLOv8 model for player detection**, combined with a **basic centroid-based tracking** algorithm enhanced by **IoU (Intersection over Union)** and **Euclidean distance** for player re-identification. Each player is given a unique `Player_ID`, and tracking is maintained frame-by-frame.



Pros:

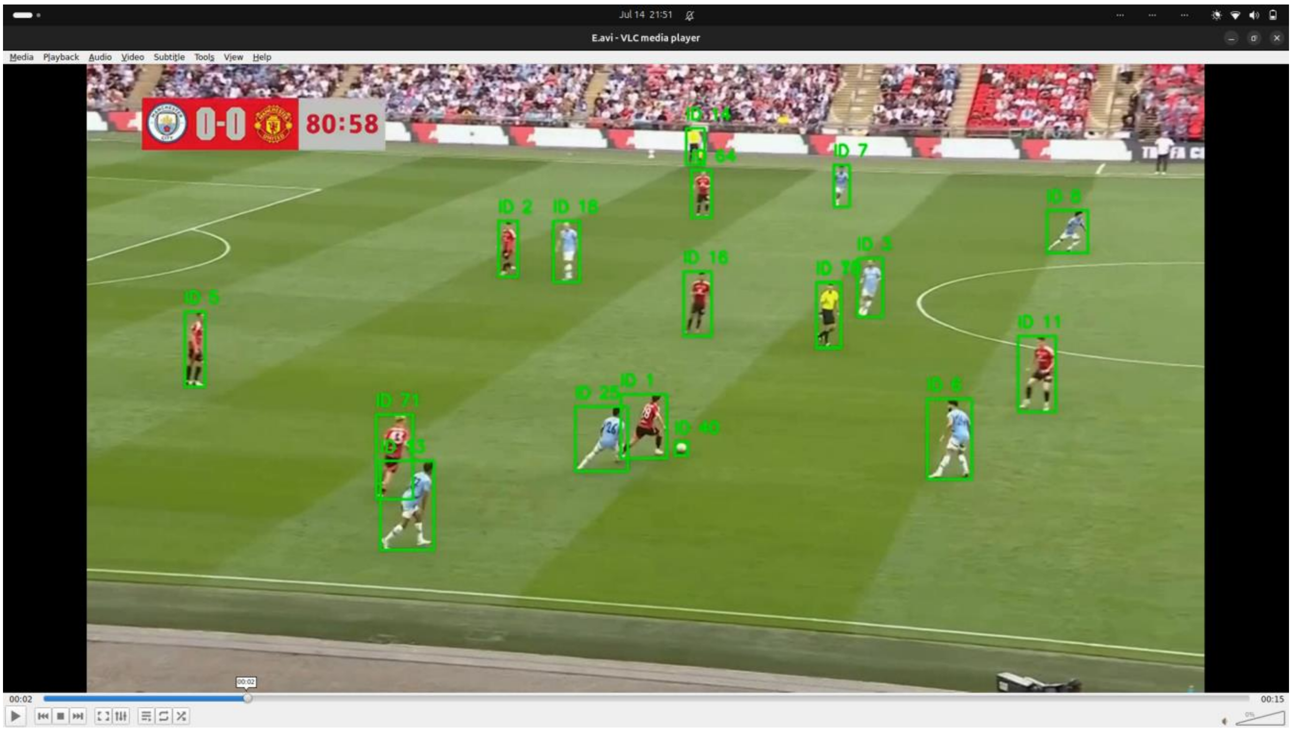
- **Efficient Detection:** YOLOv8 offers fast and accurate player detection.
- **Custom Model:** Tailored to your dataset (likely trained for football players), ensuring better performance than generic models.
- **Simple Yet Effective Tracking:** Using both **centroid distance** and **IoU** balances position and shape consistency.
- **Unique ID Assignment:** Players retain their IDs well, making analysis and logging easier.
- **CSV Logging:** Easy to use for downstream tasks like performance analysis or heatmaps.
- **Visual Feedback:** Real-time bounding boxes and IDs aid in validation.

Cons:

- **Basic Tracker:** Lacks robustness in occlusion, abrupt motion, or overlapping players.
- **No Re-ID Module:** If a player disappears and reappears, they might get a new ID.
- **Limited Temporal Consistency:** No use of Kalman filter or motion prediction.
- **Crowd Sensitivity:** Skips frame if too many detections (e.g., audience), which may miss real frames.
- **Static Thresholds:** Fixed `dist < 60` and `iou > 0.1` may not generalize to all scenes.
- **No Team Classification:** All players are treated equally—no team/role separation yet.

8) **Techniques Used**

- **Centroid Distance Matching** – track players by proximity
- **HSV Dominant Color** – detect jersey color for team ID
- **Bounding Box Height Comparison** – ensure scale consistency
- **Manual ID Assignment** – assign new ID if no match
- **Frame Skipping** – control processing load for higher FPS
- **Basic Visualization** – draw bounding boxes and ID labels.



Pros

- Simple and easy to implement
- Lightweight (no heavy models)
- Uses color for team differentiation
- Customizable tracking logic
- Can run in real-time on CPU

Cons

- No motion prediction (no Kalman filter)
- Sensitive to occlusion and lighting changes
- Prone to ID switches in crowded scenes
- Thresholds need tuning for each video

- No appearance (Re-ID) learning

9) **Techniques Used**

- **YOLOv8 + Custom Trained Model (`best.pt`)**
  - Detects players in the soccer video.
- **BoT-SORT Tracker (`botsort_custom.yaml`)**
  - Assigns consistent `Track_IDs` to players across frames.
- **OpenCV**
  - Handles video reading, drawing bounding boxes, and writing annotated video.
- **CSV Logging**
  - Logs `Frame, Track_ID, X, Y, Width, Height` every second for tracking data.

Pros

- **High Accuracy Detection**
  YOLOv8 with a fine-tuned model ensures reliable player detection.
- **ID Consistency Across Frames**
  BoT-SORT keeps IDs consistent, even during overlaps and occlusions.
- **Efficient Logging**
  Frame-level tracking data is logged once per second to reduce size.
- **Clear Visual Output**
  Green boxes with ID labels allow easy human verification of tracking.
- **Real-Time Capable**
  Optimized for reasonably fast processing using efficient models.

Cons

- **Limited Object Classes**
  Only tracks players (`classes=2`). Ball, referee, etc., are ignored.
- **Hard-Coded Parameters**
  Confidence, IOU thresholds, and FPS interval are fixed — not adaptive.
- **No Error Handling**
  If video or model paths are incorrect, the code crashes silently.
- **Single-Class Limitation**
  Difficult to distinguish between team colors or referee without additional logic.
- **No Smoothing/Post-Processing**
  Bounding boxes and IDs can jitter without a temporal filter.

10)**Techniques Used**

- **YOLOv8**: For detecting players in each frame.
- **ByteTrack**: For assigning consistent player IDs across frames.
- **Tracking-by-Detection**: Uses YOLO + Tracker per frame.
- **CSV Logging**: Saves player positions once per second.
- **OpenCV Visualization**: Draws boxes and IDs on players.

Pros

- Fast and accurate (YOLOv8).
- Tracks multiple players reliably (ByteTrack).
- Easy post-game analysis via CSV.
- Simple to visualize and debug.

Cons

- Loses identity during occlusion or overlaps (ID switch).
- No team or jersey detection.
- Tracking only while player is visible.
- Misses fast actions between logged frames.

11) **Techniques Used**

1. **YOLOv8 (Object Detection)**
    - Detects players (class 2) in each video frame.
    - `best.pt` model used (likely custom-trained).
2. **BoT-SORT (Object Tracking)**
    - Assigns unique `track_id` to each detected player.
    - Maintains player identities across frames.
3. **Custom ID Remapping**
    - Converts tracker IDs to consistent `Player_ID`s using a dictionary.
    - Tracks reappearance/disappearance status.
4. **Logging to CSV**
    - Records frame-wise player data: position, size, status.
5. **Video Annotation**
    - Draws bounding boxes and labels with `Player_ID` on output video.

Pros

- **Accurate Tracking:** BoT-SORT effectively tracks multiple players.

- **Consistent IDs:** Custom remapping ensures readable and stable player IDs.
- **Efficient Detection:** YOLOv8 is fast and optimized for real-time performance.
- **Status Monitoring:** Tracks reappearance/disappearance of players.
- **Structured Output:** Saves data in CSV for post-analysis or model training.

Cons

- **Occlusion Challenges:** Overlapping players can confuse the tracker.
- **ID Switches Possible:** Trackers may reassign IDs incorrectly on reentry.
- **Detection Class Limitation:** Only class 2 (player) is used; others like ball/referee are ignored unless customized.
- **Accuracy Depends on Model Training:** Poorly trained model may lead to missed or false detections.
- **Processing Time:** Real-time tracking is CPU intensive and may lag on large videos or high FPS.

Challenges I encountered

1. ID Interchanging in Centroid-Based Tracking

When two or more players come very close to each other, their centroids overlap or become nearly identical. This causes the tracking logic to **misidentify players**, resulting in **ID switching**. Since the matching is based on distance and appearance features (like color and height), highly similar or overlapping detections confuse the system.

2. High Frame Rate Complications (e.g., 50 FPS)

Increasing the frame rate theoretically improves accuracy by reducing motion between frames. However, it introduces **unexpected ID inflation**, where **extra or unusually large IDs** are assigned. This occurs because:

- With 50 frames in 1 second, **subtle movements or noise** in detection can be misinterpreted as new objects.
- It's difficult to **visually verify such fast transitions**, leading to unexplained behavior.

Despite this, higher frame rates often **improve detection granularity**, especially for fast-moving subjects.

3. Bounding Box Instability with DeepSORT

When using DeepSORT (or similar algorithms), the **bounding boxes sometimes expand unnecessarily** even when the player has not moved much. This happens due to:

- **Rapid frame transitions** with minor movement, leading to **predictive noise** in tracking.

- The algorithm trying to **"guess"** object motion, which may not align with actual movement.

This can result in **visual inconsistency** and tracking errors.

4. Overlapping Detections Causing Drawing Conflicts

When multiple centroids are very close, **drawing circles** around each can cause **visual clutter** or overlapping annotations. To manage this, a minimum distance threshold is applied, but this sometimes leads to **valid detections being skipped for drawing**, reducing clarity.

5. Appearance-Based Matching Limitations

Using **dominant color (HSV hue)** and **bounding box height** as identity features works well in general. However:

- Lighting changes or camera exposure affect hue reliability.
- Similar jerseys across teams or players make visual distinction difficult.

This limits the tracking performance in real-world noisy conditions.

6. Webcam Limitations in Real-Time Mode

While transitioning to real-time mode using the webcam:

- **Frame drops** or **delays** occur depending on hardware capability.
- The webcam may not deliver a consistent resolution or frame rate, affecting model accuracy.
- CPU/GPU usage can spike, leading to reduced performance.

- **If incomplete, describe what remains and how you would proceed with more time/resources:**

I explored numerous unique approaches to achieve the project goals, such as color mapping with player IDs, bounding box centroid-based tracking, circular bounding box tracking, jersey number tracking, ByteTrack, BoT-SORT, and others—each with its own strengths and limitations. I experimented with various methods to find the most effective solution. However, due to limited resources, especially the restricted GPU availability on Google Colab, I had to run everything on the CPU, which affected the efficiency of my experiments. Additionally, my college exams further constrained the time I could dedicate to the project. Despite these challenges, I gave my best effort within the given limitations. I am assuming that you also understand that there is no shortcut to achieving high accuracy, low time complexity, and optimal performance—it's a thoughtful, resource-intensive process. If given this internship opportunity, I am committed to doing my best and continuously improving.