# Person Detection and Tracking in Crowded Scenes using Classical Computer Vision Techniques

Academic Year: 2024-2025

**Realised by:**

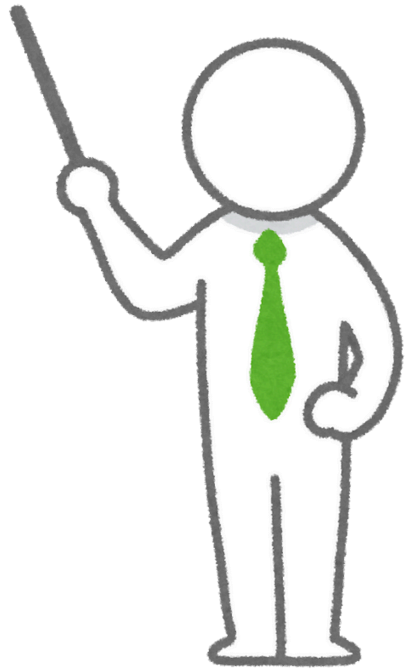
*Manon LAGARDE*
*Maria KONTARATOU*
*Chaimae SADOUNE*

**Supervised by:**

*Céline Hudelot*

# Presentation outline

- *Problem Definition*
- *Methodology*
- *Evaluation Metrics*
- *Analysis of Results*
- *Conclusion*



# Problem Definition

In dense urban environments and large-scale events, the ability to detect and track individuals is crucial for various applications such as public safety, crowd management, and behavioral studies.


## Why is this important?

- Surveillance & security
- Crowd flow analysis
- Smart city applications

## Why is this difficult?

- Scale Variations → People appear in different sizes depending on their distance from the camera.
- Occlusions → Individuals may be partially or fully blocked by others.
- Dynamic Backgrounds → Changing environmental conditions and moving cameras add complexity.

**Objective** →

1. Accurate individual detection without requiring large annotated datasets.
2. Robust tracking across frames, minimizing identity switches and false detections.
3. Computational efficiency, enabling real-time or near-real-time performance in practical applications.

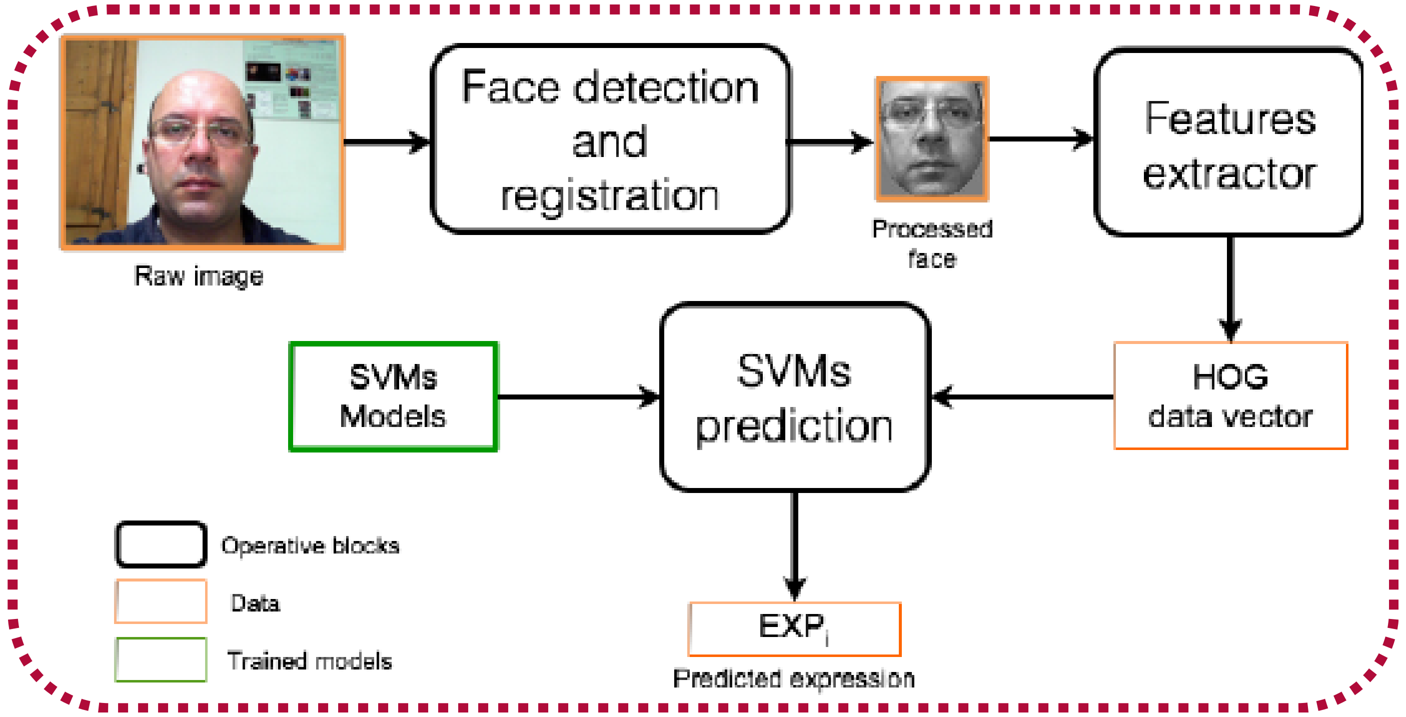
# Methodology

The proposed methodology is based on classical computer vision techniques that balance accuracy and computational efficiency. The selected approaches are :

**Pedestrian Detection using HOG and SVM**

Pedestrian Detection and Tracking using HOG and Centroid Tracking

Hybrid Pedestrian Tracking Pipeline




- HOG captures edge-based features of pedestrians effectively.
- SVM provides accurate classification with low computational overhead.

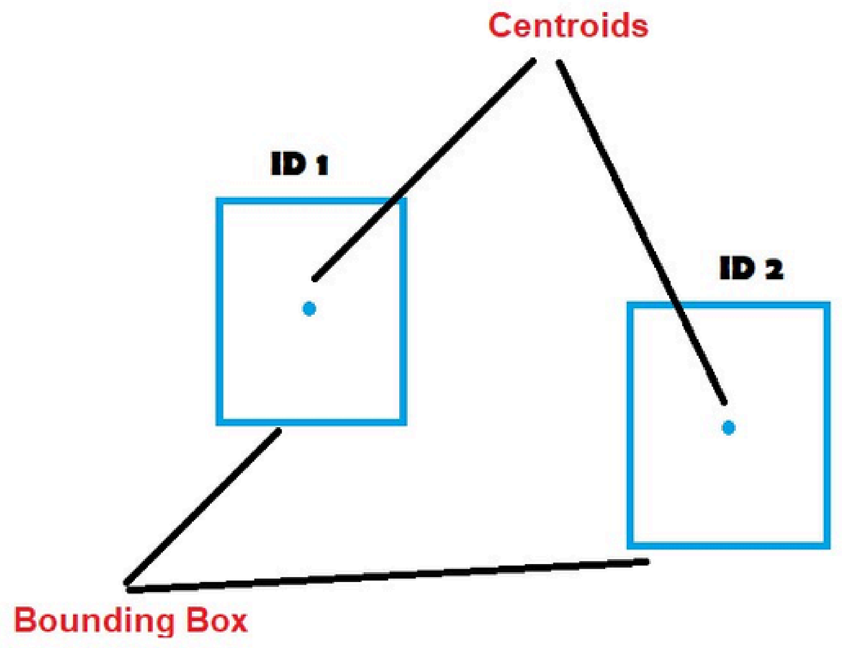
# Methodology

The proposed methodology is based on classical computer vision techniques that balance accuracy and computational efficiency.
The selected approaches are :

Pedestrian Detection using HOG and SVM

**Pedestrian Detection and Tracking using HOG and Centroid Tracking**

Hybrid Pedestrian Tracking Pipeline




- Detections are associated across frames based on centroid movement.
- Well-suited for moderate crowd densities with low computational cost.

# Methodology

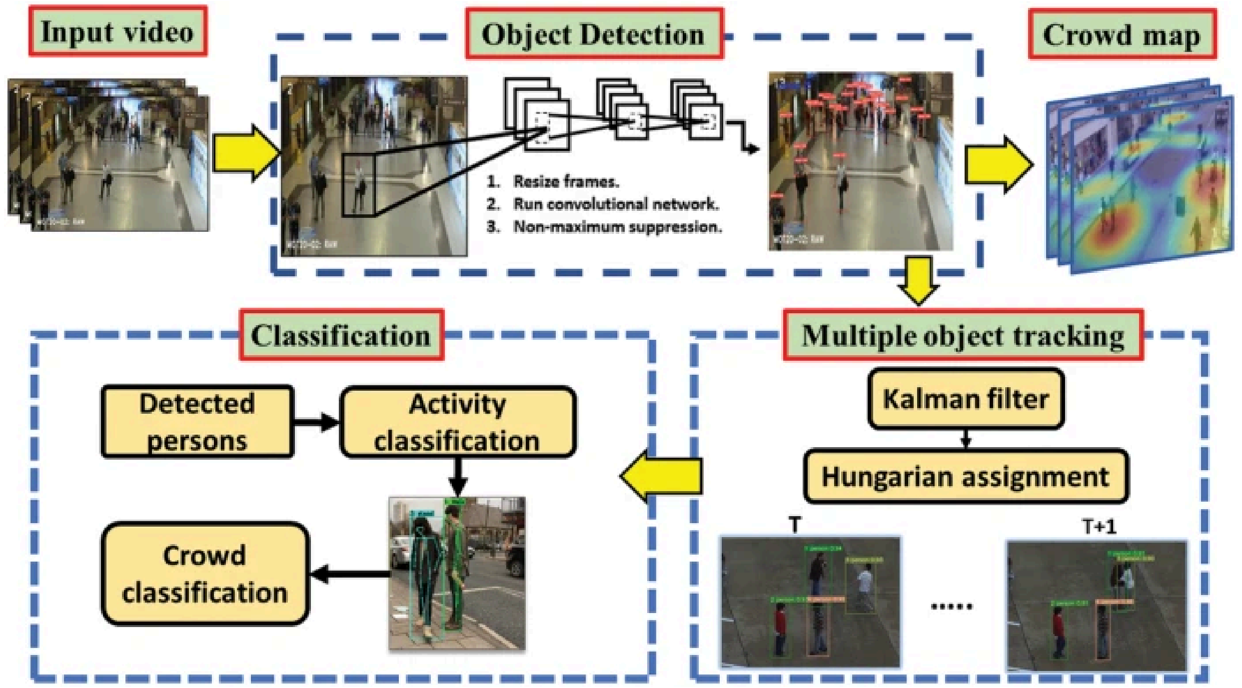
The proposed methodology is based on classical computer vision techniques that balance accuracy and computational efficiency. The selected approaches are :

Pedestrian Detection using HOG and SVM

Pedestrian Detection and Tracking using HOG and Centroid Tracking

## Hybrid Pedestrian Tracking Pipeline

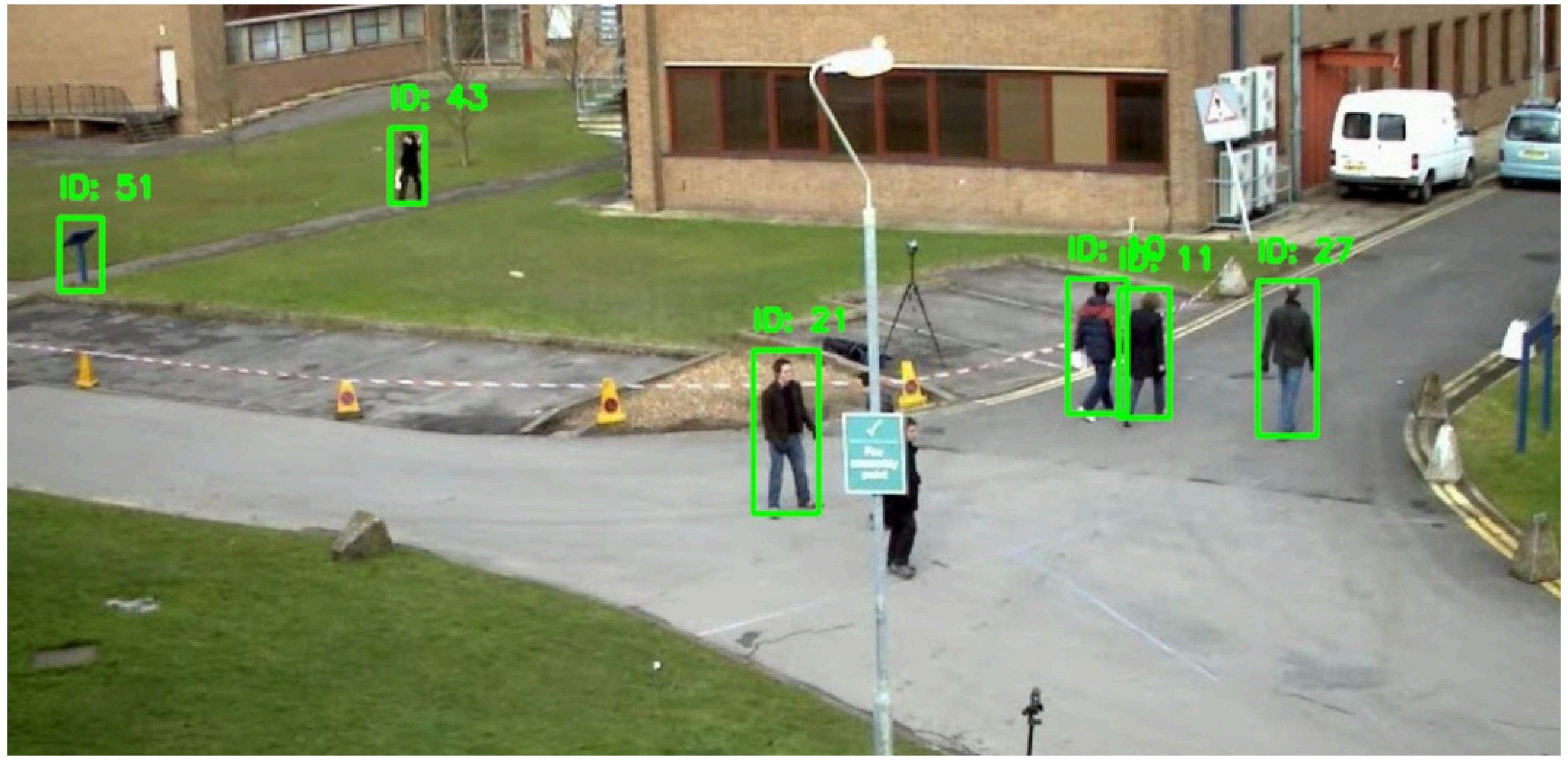
Background Subtraction, HOG + SVM Detection, and Kalman-Hungarian Tracking



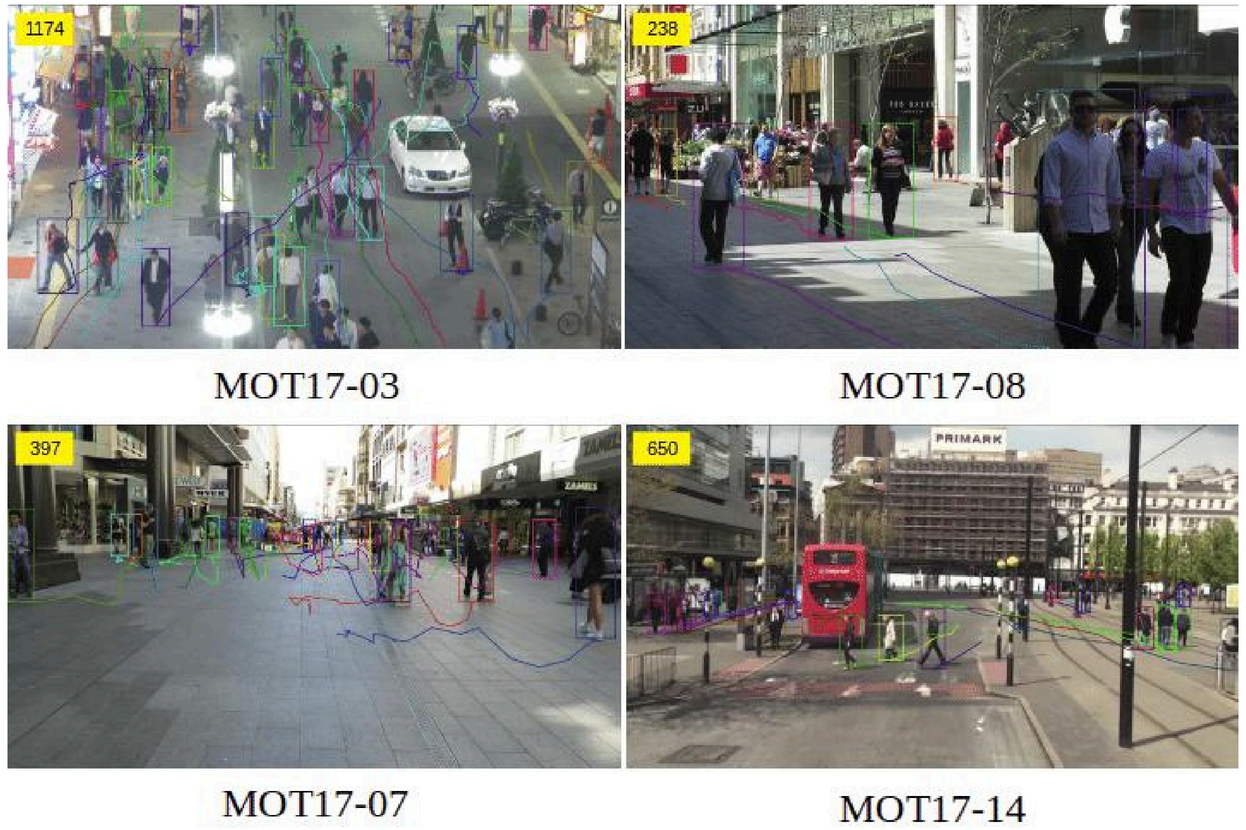

- **Background Subtraction (MOG2) →** Removes static elements and detects moving objects
- **Pedestrian Detection (HOG + SVM)**
- **IoU Filtering →** Merges overlapping detections from MOG2 and HOG to improve accuracy
- **Kalman Filter Prediction** → Estimates the next position of pedestrians based on motion history
- **Hungarian Algorithm Matching** → Matches new detections to existing tracks and updates Kalman if match is found

# DataSet Used

To evaluate the performance of our pedestrian detection and tracking methods, we rely on well-known benchmark datasets that reflect real-world scenarios.




**PETS2009**




**MOT Dataset**

Before applying our detection models, we prepare the datasets through several preprocessing steps to enhance their suitability. After preprocessing, these datasets serve as the foundation for training and testing

# Evaluation Metrics :

To evaluate the performance of our pedestrian detection and tracking methods, we used key evaluation metrics :

- **Precision & Recall** – Measure the model's ability to correctly detect pedestrians while minimizing false positives and false negatives.
- **F1 Score** – Balances precision and recall to provide an overall performance measure.
- **Intersection over Union (IoU)** – Evaluates how well predicted bounding boxes overlap with the ground truth.
- **Multi-Object Tracking Accuracy (MOTA)** – Penalizes false positives, false negatives, and identity switches.
- **Multi-Object Tracking Precision (MOTP**) – Measures how accurately detected objects align with ground truth over time.
- **Processing Time per Frame** – Determines real-time feasibility.

# Evaluation Metrics :

To test the robustness of our models, experiments were conducted under diverse conditions :

- **Static & dynamic backgrounds** – Static scenes are easier for background subtraction, while dynamic scenes introduce motion-based detection challenges.
- **Different crowd densities** – Sparse pedestrian environments are easier to track, while dense crowds introduce occlusions and identity switches.
- **Scale variations** – People appear at different scales based on distance, challenging fixed-size feature extractors like HOG.

Dataset Used :

- **PETS09-S2L1** – A moderately crowded scene with occlusions.
- **PETS09-S2L2** – A highly dense crowd, making detection and tracking significantly harder.

# Results Overview :

| Model | Video | Precision | Recall | F1 Score | IoU | Dice Score | MOTA | MOTP |
|---|---|---|---|---|---|---|---|---|
| HOG + SVM | PETS09-S2L1 | 0.002 | 0.0013 | 0.0016 | 0.5427 | 0.0016 | N/A | N/A |
| Hybrid Model | PETS09-S2L1 | 0.014 | 0.0118 | 0.0128 | 0.5639 | 0.0128 | -0.8241 | 0.5697 |
| HOG + SVM | PETS09-S2L2 | 0.0013 | 0.0004 | 0.0006 | 0.5226 | 0.0006 | N/A | N/A |
| Hybrid Model | PETS09-S2L2 | 0.0079 | 0.003 | 0.0044 | 0.5516 | 0.0044 | -0.3775 | 0.5631 |

*Table - Evaluation Metrics Overview for Pedestrian Detection and Tracking*

The **Hybrid Model (MOG2 + HOG + Kalman)** showed better precision and recall than the baseline model (HOG + SVM), but performance remains limited.

- Low Precision & Recall indicate frequent false positives and missed detections, limiting reliability.
- IoU (~0.55) suggests detections are somewhat aligned with ground truth but box placement is inconsistent.
- Negative MOTA scores highlight frequent identity switches and poor tracking stability, especially in high-density scenes.
- MOTP (~0.56) shows that when tracking succeeds, bounding box alignment is reasonable, but tracking failures dominate.
- PETS09-S2L2 (dense crowd) worsens performance, with recall dropping to 0.0030, making tracking unreliable.

While **classical methods provide a computationally efficient approach**, visual verification shows that person detection worked despite the weak tracking performance. Occlusion handling, feature extraction, and tracking consistency still require improvements for real-world applications.

# Conclusion :

**Advantages :**

- Lightweight and interpretable approach using HOG + MOG2 + Kalman filtering, making it suitable for low-resource applications.
- Real-time pedestrian detection and tracking without requiring deep learning.
- Visual observation confirmed successful pedestrian detection, even though numerical scores were low.

**Limitations :**

- Struggles with occlusions and dense crowds, leading to identity switches and false detections.
- Tracking is unstable, as seen in negative MOTA scores, especially in high-density scenarios.
- Background subtraction introduces false positives, affecting detection accuracy.

# Conclusion :

**Next steps :**

- Improve feature extraction by integrating Local Binary Patterns (LBP) or wavelet-based features to enhance detection.
- Refine tracking algorithms using better object association techniques to reduce identity switches.
- Implement adaptive background modeling to reduce false positives in motion-based detection.

**Real-World Applications :**

- Surveillance & Security – Enhancing crowd monitoring and public safety in urban areas.
- Traffic Monitoring – Pedestrian movement analysis for smart city planning and road safety.
- Crowd Analysis – Understanding pedestrian flow in public spaces, malls, and transportation hubs.

**Classical computer vision techniques offer a viable solution for pedestrian detection and tracking in low-resource environments. Despite challenges with occlusions and identity tracking, the approach provides a foundation for improvement. Enhancing feature extraction, tracking stability, and background modeling can make it a reliable alternative for real-time applications without deep learning.**

# Thank You