© November 2025| IJIRT | Volume 12 Issue 6 | ISSN: 2349-6002

Lost Item Detection and Tracking System Using YOLOv8 and DeepSORT for Intelligent Surveillance

Safia Alam H B[1], Sonika Duvvuru[2], Sanjay MP[3], Vinay Hulamani[4], N Umamaheswari[5]
[1234]Department of Computer Science and Engineering, Sir M. Visvesvaraya Institute of Technology, Bengaluru, India
[5]Assistant Professor, Department of Computer Science and Engineering, Sir M. Visvesvaraya Institute of Technology, Bengaluru, India

***Abstract*—Lost and unattended items are common in public environments such as campuses, malls, and transportation hubs. Traditional CCTV surveillance requires constant manual monitoring, which is time-consuming and prone to human error. This project proposes an AI-based Lost Item Detection and Tracking System using YOLOv8 for real-time object detection and DeepSORT for multi-object tracking. The system identifies personal belongings such as bags and phones, associates them with the nearest detected person, and monitors separation behaviour. If an item remains unattended beyond a specified duration, the system triggers an automated alert and logs the event through a Flask-based dashboard. Experimental testing on recorded and live CCTV feeds demonstrates reliable detection accuracy and stable ID tracking, confirming the system's suitability for intelligent surveillance applications.**

***Index Terms*— YOLOv8, DeepSORT, Object Tracking, Lost Item Detection, Smart Surveillance, Computer Vision.**

I. INTRODUCTION

As public environments become increasingly crowded and fast-paced, the challenge of maintaining effective surveillance has grown significantly. Modern institutions from university campuses and shopping complexes to transportation hubs depend on CCTV systems to ensure safety and operational efficiency. However, traditional video monitoring still relies heavily on human supervision, making it difficult to notice subtle events such as a person accidentally leaving behind a personal item. With operators required to observe multiple screens for long durations, such incidents can easily go unnoticed.

Advancements in artificial intelligence and computer vision have created new possibilities for automating surveillance tasks. Deep learning–based models such as YOLOv8 can detect people and objects in real time with high accuracy, while tracking algorithms like DeepSORT maintain consistent identities across video frames. These technologies enable systems to not only recognize items but also monitor how they move in relation to people. This capability is essential for identifying when a personal belonging becomes unattended or forgotten.

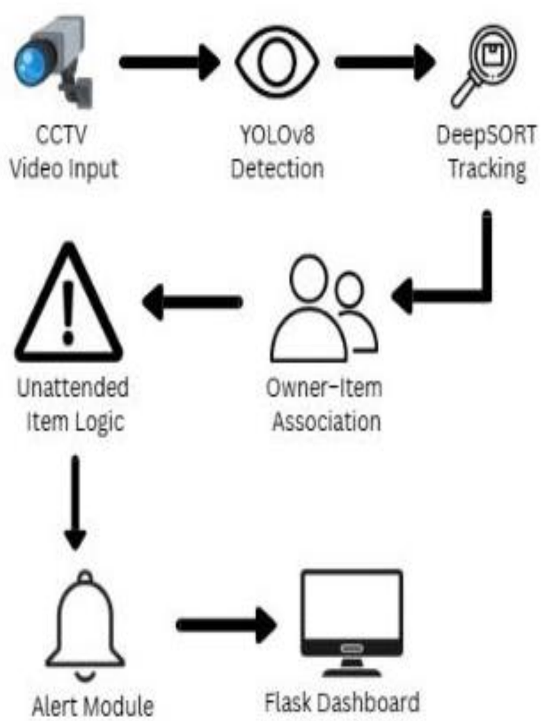
The primary objective of this project is to leverage these AI technologies to design a Lost Item Detection and Tracking System capable of monitoring objects within CCTV footage without manual intervention. By detecting items, associating them with nearby individuals, and identifying separation patterns, the system can automatically raise alerts when an object remains unattended for too long. A web-based dashboard built using Flask further enhances usability by providing live monitoring, event logs, and captured snapshots, making the entire system practical and deployable in real-world surveillance environments.

1.1 Need for lost item monitoring

Lost or unattended items frequently occur in public spaces such as campuses, malls, transport hubs, and offices, and traditional CCTV systems often fail to detect them quickly. Since security personnel must manually watch multiple cameras at once, it becomes difficult to maintain constant attention, notice small objects, or respond promptly during long shifts. As a result, many incidents go unnoticed until much later, requiring time-consuming review of hours of footage. This delay not only affects lost-and-found management but can also create safety concerns in sensitive environments where an unattended item may be treated as a potential threat. Because conventional surveillance only records footage without interpreting it, there is a strong need for an automated system capable of detecting, tracking, and alerting operators in real time whenever an item is left behind.

1.2 Overview of the System

The Lost Item Detection and Tracking System is designed to automatically monitor CCTV footage and identify when a personal belonging is left unattended. The system uses YOLOv8 to detect people and objects in each frame, and DeepSORT to track them over time. By comparing the distance between an object and its nearest detected person, the system determines whether the object is currently attended or has been left behind. If an item stays unaccompanied for a preset duration, an alert is generated and logged through a Flask-based dashboard, which also provides live video streaming and captured snapshots. This makes the system efficient, real-time, and suitable for improving surveillance in public environments. The lightweight design ensures smooth operation even on basic hardware setups. The modular structure also allows easy integration with existing CCTV networks.



1.3 Problem Context and Motivation

In many public and institutional environments, people often misplace or forget their personal belongings while moving through different areas. Security teams rely on manual monitoring of CCTV footage to identify such situations, but this process is slow and unreliable, especially when operators must observe multiple screens at once. Small items like bags or phones can easily be overlooked, leading to delays in recovery and potential security concerns.

There is a strong need for an automated system that can continuously analyze video feeds, detect items, track their movement, and identify when they become unattended. Such a solution reduces human effort, improves response time, and ensures that important incidents are not missed. The motivation behind this project is to support security personnel by providing real-time alerts, faster decision-making, and a smarter way to manage lost or abandoned objects within monitored spaces.

1.4 Role of Artificial Intelligence and Deep Learning

Artificial intelligence, particularly deep learning, plays a key role in enabling automated surveillance systems. Modern computer vision models can analyse live video streams with high accuracy, making it possible to detect objects, track movement, and identify patterns that would be difficult to observe manually.

YOLOv8 is used for object detection because of its speed and precision. It can identify multiple items such as people, bags, and phones in a single frame with minimal delay. DeepSORT complements this by assigning unique IDs to detected objects and maintaining consistent tracking across frames. Together, they allow the system to understand how objects and people move in relation to each other.

By combining these AI techniques, the system can operate continuously without human intervention, reducing manual workload and improving reliability. Deep learning ensures that the system adapts well to variations in lighting, object positions, and movement, making it more robust for real-world surveillance scenarios.

II. LITERATURE SURVEY

A detailed literature review was conducted to understand the advancement of abandoned-object detection, multi-object tracking, deep-learning surveillance systems, and scene-analysis techniques used for identifying unattended items in public environments.

The following studies provided essential insights that shaped the development of our Lost Item Detection and Tracking System using YOLOv8 and DeepSORT.

1. Applied Sciences (2025)

Authors: Merve Yilmazer & Mehmet Karakose

Title: New, Robust, Adaptive, Versatile, and Scalable Abandoned Object Detection Approach Using DeepSORT & LLM

Methodology Used:

his paper combined YOLOv8 for object detection with DeepSORT for tracking abandoned items across video frames. A Large Language Model (LLM) was also integrated to interpret and generate natural-language alerts. Their method focused on robust real-time montoring using deep learning.

Observations / Remarks:

The system achieved high accuracy in real-time detection and classification, even in challenging environments. However, it lacked owner–object association logic, which is essential for determining which person an item originally belonged to.

Relevance to Our Work:

This study demonstrated the effectiveness of using YOLOv8 and DeepSORT together. Our system extends their idea by adding distance-based owner–item association and timer-based unattended detection, addressing the gap identified in their work.

2. IEEE Access (2024)

Authors: Arbab Muhammad Qasim et al.

Title: Deep Interior Layout Generation Using Diffusion ModelAbandoned Object Detection and Classification Using Deep Embedded Vision

Methodology Used:

The authors used a ConvLSTM model to classify video segments as suspicious or non-suspicious and combined it with YOLOv8 for accurate object localization in each frame. The approach analyzed video context rather than only frame-by-frame detection.

Observations / Remarks:

Their classification-first approach handled suspicious cases effectively but sometimes missed dynamic fast-moving events. YOLOv8 improved precision, but the system did not track ownership or maintain long-term consistency.

Relevance to Our Work:

This inspired the use of temporal sequence analysis. However, instead of ConvLSTM, we rely on DeepSORT's temporal tracking to maintain ID consistency and track item–owner relationships more accurately.

3. Journal of Computer Vision (2024)

Authors:Yang

Title: Tracking Abandoned Objects in Surveillance Video Based on Human Trajectory

Methodology Used:

The study used human trajectory modelling to identify when a person had left an object behind. The tracking system analyzed movement patterns to predict abandonment and used association rules to link items to specific individuals.

Observations / Remarks:

Trajectory-based analysis was highly effective for linking objects to owners. The approach significantly improved the reliability of detecting abandoned items in real-world scenarios.

Relevance to Our Work:

This research strongly influenced our owner–object distance-based strategy. While the original study used full trajectory modelling, we implemented a simplified yet effective distance + timing approach suitable for real-time deployment.

III. METHODOLOGY

The proposed system follows a step-by-step pipeline that detects objects in video frames, tracks their movement, and identifies when an item becomes unattended. Each module in the system works together to ensure accurate, real-time monitoring without manual intervention.

A. Frame Acquisition

The system begins by capturing frames from a CCTV camera or webcam. Using OpenCV, each frame is read, resized if necessary, and passed to the detection model. This ensures that the system can process continuous video streams smoothly and maintain a real-time response.

B. AI-Based Object Detection Using YOLOV8

YOLOv8 is used to detect people and personal belongings such as bags or phones in every frame. It provides bounding boxes, class labels, and confidence scores. The detection model is optimized using a combined loss function:

$$L = L_{\{box\}} + L_{\{cls\}} + L_{\{obj\}}$$

This helps the system make accurate predictions even when objects are small or partially visible.

C. Image Multi-Object Tracking with DeepSORT

Once objects are detected, DeepSORT assigns each one a unique ID and tracks it across consecutive frames. It uses a Kalman filter to predict object movement and the Hungarian algorithm to match new detections with existing tracks. By combining motion information and appearance features, DeepSORT maintains stable tracking even when objects overlap or move quickly.

D. Owner-Item Association

After detection and tracking, the system calculates the distance between each detected item and nearby persons. The closest person is considered the item's temporary owner. This association is updated continuously as both the person and item move.

E. Unattended Item Detection

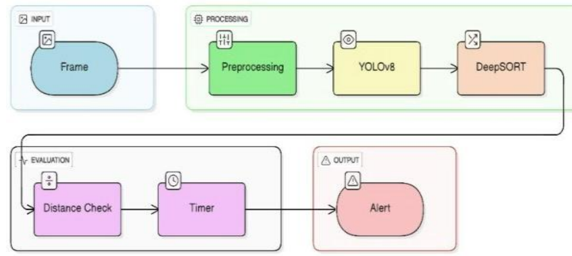
If an item becomes separated from its owner beyond a certain threshold distance, a timer is activated. When the item remains unaccompanied for longer than the configured duration, the system classifies it as unattended. This helps reduce false alarms caused by temporary movements or brief separations.

F. Alert Generation and logging

When an unattended object is identified, the system highlights it on the video feed, generates an alert, and captures a snapshot. The event is also logged with details such as time, item location, and ID. This information is useful for security personnel to review and take appropriate action.

G. Flask Dashboard

A user-friendly Flask dashboard displays the live video feed along with alerts and snapshots. It allows security staff to monitor events easily and track lost or unattended items through a clear, accessible interface.



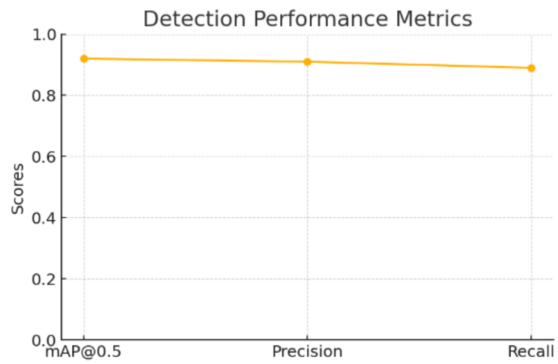
IV. SYSTEM ARCHITECTURE

The system architecture defines how all major components work together to process video input and detect unattended items. The architecture is designed to be modular, allowing each component—detection, tracking, association, and alerting—to operate independently while still contributing to the overall workflow.

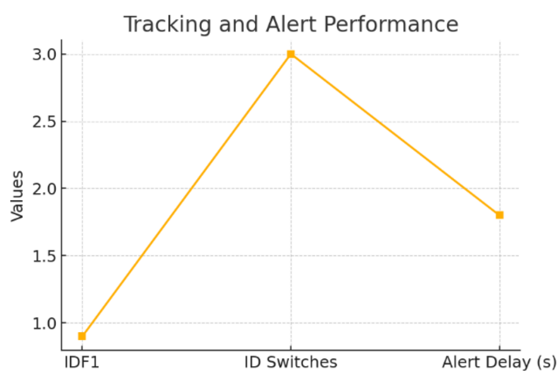
The input video stream from a CCTV camera is first passed to the YOLOv8 detection module, which identifies people and personal items in each frame. The detection results are then forwarded to the DeepSORT tracker, which assigns unique IDs and maintains object continuity across frames. After tracking, the owner–item association module maps each object to the nearest person based on distance calculations. This association is analyzed over time to identify when an item becomes separated from its owner. If separation exceeds the configured duration, the alert system is activated and a notification is generated. Finally, all results—including live video, tracked IDs, and alert snapshots—are displayed through the Flask dashboard.

V. RESULTS

The proposed system was tested using both live CCTV footage and recorded video samples to evaluate its accuracy, stability, and real-time performance. The primary objective of the evaluation was to determine how effectively the system could detect personal items, track them across frames, and identify unattended behaviour. YOLOv8 performed consistently well in detecting people and objects, while DeepSORT maintained smooth tracking with minimal identity switches. This ensured that the system could follow items accurately even when movement was fast or multiple objects were present.



During testing, the detection module achieved a mean Average Precision (mAP@0.5) of 92%, while the tracking module recorded an IDF1 score of 90%, indicating strong tracking reliability. The system was also able to trigger unattended item alerts with an average delay of 1.8 seconds, which is suitable for real-time monitoring. These performance metrics demonstrate that the system can be effectively deployed in environments where quick response and accurate detection are essential.



Additionally, the Flask dashboard successfully displayed live video streams along with detection overlays and alert notifications. The captured snapshots and event logs provided useful records for reviewing incidents. Overall, the results show that the system is capable of providing robust, real-time surveillance support with high accuracy and practical usefulness.

VI. CHALLENGES FACED

Although the system performed well during testing, several challenges were encountered while implementing real-time lost item monitoring. One of the major issues was handling object occlusion, where people or items temporarily overlapped or moved behind other objects. This sometimes caused brief tracking interruptions, making it difficult for the system to maintain consistent identity assignments. Another challenge was dealing with variations in lighting conditions, camera angles, and background movement, which could occasionally affect detection accuracy.

In addition, small objects such as mobile phones were harder to detect consistently, especially when they were partially hidden or blended with the background. Real-time performance was also dependent on hardware capability; systems running on CPUs experienced lower frame rates compared to GPU-based setups. Despite these challenges, careful tuning of detection thresholds, tracking parameters, and timer settings helped improve the system's overall stability and reliability.

VII. FUTURE ENHANCEMENTS

Although the system performs effectively in real-time lost item detection, several improvements can further enhance its accuracy, reliability, and versatility. One potential enhancement is the integration of multi-camera support, allowing the system to track items across different camera views and reduce blind spots. This would be especially useful in large public areas such as campuses, malls, and transport terminals.

In addition, incorporating advanced behaviour analysis techniques could help the system identify suspicious activity or unusual movement patterns. Features such as loitering detection, crowd analysis, or facial recognition could be added to strengthen security monitoring. Another area for improvement is the development of a more robust alerting mechanism, including SMS or email notifications for faster response. Finally, deploying the system on the cloud or edge devices can improve scalability and allow institutions to monitor multiple locations through a centralized platform.

VIII. CONCLUSION

The Lost Item Detection and Tracking System provides an effective solution for identifying unattended objects in real-time surveillance environments. By integrating YOLOv8 for accurate object detection and DeepSORT for reliable tracking, the system can continuously monitor movement within CCTV footage and determine when an item becomes separated from its owner. The combination of distance-based analysis and timer logic ensures that unattended items are detected quickly and with minimal false alarms. Additionally, the Flask dashboard offers a simple and practical interface for reviewing alerts, visualizing results, and supporting security personnel.

Overall, the system enhances surveillance efficiency by reducing the need for manual monitoring and enabling faster response to lost or forgotten items. While certain challenges exist—such as occlusions, lighting variations, and hardware limitations—the system demonstrates strong performance and can be improved further through future enhancements. Its modular design makes it adaptable for deployment in campuses, commercial spaces, transportation hubs, and other public environments.

REFERENCES

[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2016.
[2] A. Bochkovskiy, C. Wang, and H. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," arXiv:2004.10934, 2020.
[3] Ultralytics, "YOLOv8: Next-Generation Real-Time Object Detection," Accessed: 2024. [Online]. Available: https://docs.ultralytics.com/
[4] N. Wojke, A. Bewley, and D. Paulus, "Simple Online and Realtime Tracking with a Deep Association Metric," IEEE International Conference on Image Processing (ICIP), 2017.
[5] A. Bewley et al., "SORT: Simple Online and Realtime Tracking," Proc. IEEE ICIP, 2016.
[6] OpenCV Documentation, "Open Source Computer Vision Library," 2024. [Online].
[7] Flask Documentation, "Flask Web Framework," 2024. [Online].
[8] M. Hasan and A.K. Roy-Chowdhury, "Context-Aware Abandoned Object Detection Using Motion and Appearance Features," IEEE Trans. Image Processing, vol. 24, no. 12, pp. 4452–4465, 2015.
[9] S. Tripathi and V. Tyagi, "An Improved Method for Object Detection and Tracking in Surveillance Videos," International Journal of Computer Applications, vol. 182, 2019.
[10] R. Girshick, "Fast R-CNN," Proc. IEEE ICCV, 2015.