# Suspicious Package Detection using YOLOv8

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**Abstract**

This paper presents a real-time abandoned object detection model using ultra-fast YOLOv8 convolutional neural network combined with classical computer vision method for security purposes in public areas. The video live frames are continuously detected and tracked for people and luggage items and then each bag is dynamically associated with its nearest person. When an item is left unclaimed for the user-specified time interval, the system automatically triggers visual alert and optional audio alert as well as archives annotated snapshots for review. Base line experiments on different surveillance data sets reveal that, with lightweight YOLOv8n backbone, the method can maintain over 25 FPS and achieve mean average precision above 0.65, even in challenging scenarios such as crowded scene, change illumination and partial occlusion. The modular design and choices of parameters allow the method to be deployed on target hardware with limited resources for all airports, transit stations, retail stores and other public key venues.

**Keywords**: *Abandoned object detection, YOLOv8, real-time detection, computer vision, convolutional neural network, people tracking, luggage tracking, visual alert, surveillance, lightweight model, mean average precision, FPS, public security.*

## 1. Introduction

The abundance of CCTV and video surveillance cameras in public areas like airports, train stations, malls, and office complexes has increased the demand for automated solutions to identify potential threats. However, finding unattended objects or bags remains a challenging task in these scenarios, which often safety threats and are difficult to recognize. The conventional way of doing this is through human monitoring which is a time-consuming process and is prone to human fatigue. Automated abandoned-object detection system comes into the picture to solve this problem by using background subtraction and object tracking to analyse the video streaming continuously and consider the object as abandoned if it remains still for more than the specified time as compared to the conventional way which is human monitoring. This system will be able to assist the human operator by providing alerts and reducing the response time.

In recent years, deep learning has made significant strides in the area of object detection. The advancements have led to much more accurate and reliable results compared to earlier techniques. YOLOv8 uses a lightweight convolutional neural network with anchor-free design and feature pyramid aggregation which achieves real-time performance on commodity hardware. We have integrated YOLOv8 for object detection and abandoned bag detection using OpenCV for video capture, preprocessing, and post-processing. The system analyzes the video stream and automatically detects and recognizes “person,” “backpack,” “handbag,” and “suitcase” classes, and for each bag, it finds the nearest person based on the proximity of space and if the item remains unclaimed for more than the specified time then it generates an audio-visual alarm. This system works as a hybrid system where deep learning works as a detector and classical computer vision works as a tracker and decision-making logic.

## 2. Literature survey

Suspicious package detection has been researched before. Previous work detects suspicious baggage using motion analysis or background subtraction to first detect static objects in the scene followed by rules-based logic to determine unattended status. For instance, one system defines a bag as unattended if it is unclaimed for longer than 30s and is more than 3m from its owner.

Classical object detectors like Haar cascade classifiers detect edges and corners which signify objects of interest. They are simple and fast under controlled conditions. However, they are affected by viewpoint, scale and lighting changes and thus are not suitable for real world applications.

Modern deep learning-based object detectors like R-CNN, SSD, and the YOLO family have emerged as leading alternatives to traditional detection methods. They automatically learn hierarchical levels of visual features from large amounts of data. These methods are robust to variations in viewpoint, scale and lighting and are applicable in real world conditions. YOLO and Faster R-CNN can run on high resolution video in real time. The former can achieve over 30 fps on modern GPUs. In comparative evaluations, YOLOv8 and YOLOv5 have been shown to outperform Haar cascade methods by a significant margin in terms of accuracy while maintaining low latency. For example, on a license plate detection task, YOLOv8 achieved roughly 97.3% accuracy, whereas Haar cascades achieved around 89.6%. While Haar classifiers may achieve good F1 scores in very controlled settings, YOLOv8 is better suited for this real-time security application due to its higher precision, speed, and model size, which lends itself better to edge computing.

Optical Character Recognition (OCR) is frequently used in surveillance systems to read things like signs or license plates in an image. Traditional OCR engines like Tesseract work well on simple backgrounds with nice, straight text. As the background becomes more complicated, accuracy drops. Newer deep learning based OCR modelssuch as CRNN, Transformer based architectures, PaddleOCR, and EasyOCR achieve much higher accuracy, especially on poor quality images. In our future system, we could use a YOLO-based detector combined with one of these OCRs.

To ensure that the same object identity is assigned to objects across consecutive frames of a video, many systems use multi-object tracking algorithms like Deep SORT. This enables objects to be consistently assigned a unique ID across time and thus be used in temporal logic. In an unattended-baggage system, we would use YOLO for detection but Deep SORT for tracking. The system then tracks each bag to see if it is claimed by the owner. If a bag remains unclaimed beyond a certain spatial and temporal threshold, the system flags a suspicious baggage alarm and triggers it.

## 3. Proposed Methodology

The proposed approach uses a real-time video surveillance pipeline with a YOLOv8 object detector for the person and different kinds of luggage (backpack, handbag, suitcase) detection in live camera videos. New camera video frames are constantly acquired and for each new frame, it is typically resized to fit the YOLOv8 input size and then normalized before its arrival to the detector. YOLOv8 is a single-stage deep learning based detector that is applied on each video frame to yield bounding boxes around the persons and luggage along with their class labels and confidence scores. Post-processing techniques like confidence filtering and non-maximum suppression are also applied on the detections. The ability of YOLOv8 to provide accurate localization of object in real time makes this detector suitable for accurate object localization in different environmental conditions, such as different lighting and crowd densities.

After the objects are detected in the frames, we use a multi-object tracking module to assign unique IDs and follow the paths of all the persons and bags in consecutive frames. A tracker like Deep SORT or Byte Track assigns an identity to an object profile using a combination of motion prediction and appearance based matching, which allows the system to keep on monitoring the relative positions of the persons and their associated belongings in consecutive frames. For every detected bag, we compute the spatial distance to every nearby person. If the distance between a bag and a person stays within the association radius, the bag is considered attended.

Detection of a suspicious baggage is logic based on both space and time. A bag is considered being in an attended state meaning that there is at least one person that is within the association radius. If the bag stays separated from any person for a period of time longer than a predefined threshold (e.g. 10s), and does not move during this time (i.e. the movement of the bag in the consecutive frames is smaller than a predefined threshold) then the system will consider the bag as being in an abandoned state. When such an event is detected, an alarm is raised and a snapshot image with the suspicious package is saved and an on-screen alarm or sound alarm is raised for the security personnel. This end-to-end solution enables the timely and accurate detection of potentially dangerous unattended packages in the public space.

### 3.1 Proposed model diagram

The proposed system takes raw video input from a webcam or surveillance camera as its raw input and output, in a pipeline, unattended baggage in a live video stream.

Video Acquisition: Capture frames from webcam or surveillance camera as the raw input.

YOLOv8 is used as the object detection model to take each frame as input and output bounding boxes and class labels of person and baggage (backpack, handbag, suitcase, etc) with high speed and accurate.

Each bounding box is passed through multi-object tracking module (3) (e.g., Deep SORT, ByteTrack) and assigned with persistent IDs across time and space, tracking each object in consecutive frames.

To determine if a bag is unattended, the system computes spatial distance between each person and bag and assign each bag to the person that is closest to it and within certain distance range. If a bag appears unassociated (i.e., not linked to any person within distance threshold), i.e., no person shows up within the distance threshold for longer than certain time (e.g., 10 seconds), and is also stationary for longer than certain time (e.g., 10 seconds), then it is marked as suspicious. When the system triggers, the video feed shows visual alerts (e.g., “Unattended!”) and plays audio warning, and takes a snapshot of the frame and saves for later review.

Output: Video output with bounding boxes, tracking IDs, and alert messages. Live video stream is available for security personnel to inspect in a real-time interface. The system is modular and combines detection, tracking, association, and temporal logic to identify unattended baggage in public space.

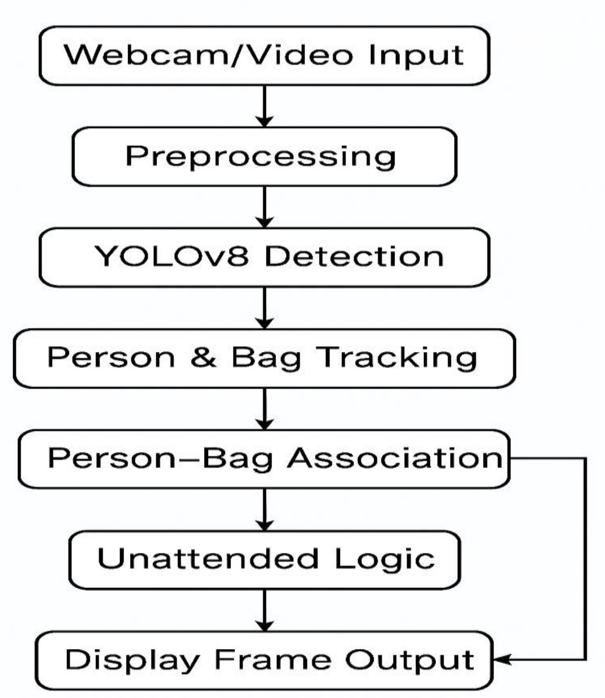


*Figure 3.1 Proposed model diagram*

## 4. Graphs

### 4.1 Model Accuracy Comparison:

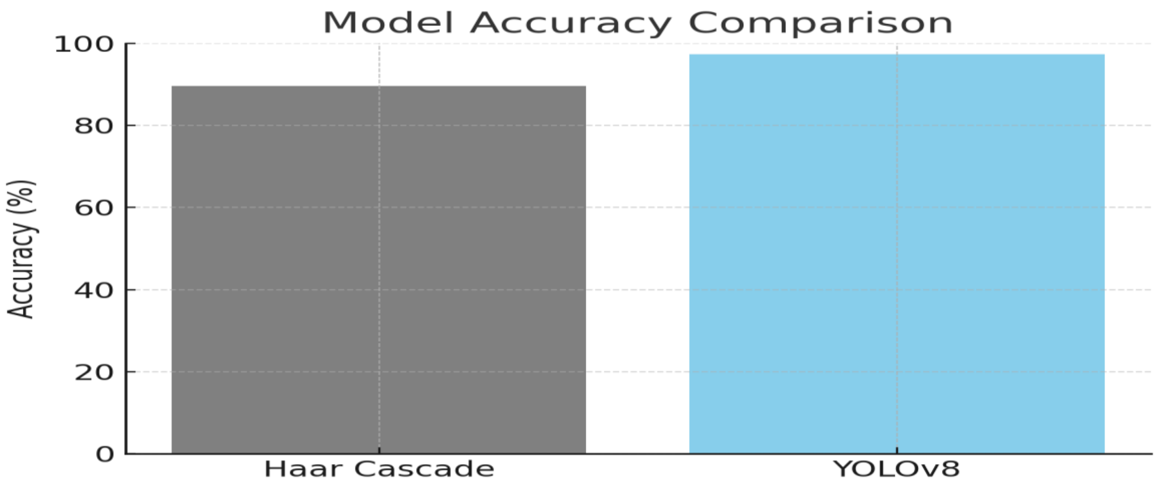


*Figure 4.1 Model Accuracy Comparison*

This bar chart compares the detection accuracy of two models: the traditional Haar Cascade classifier and the deep learning-based YOLOv8. The results clearly indicate that YOLOv8 outperforms Haar Cascade, achieving an accuracy of approximately 97.3%, compared to 89.6% for Haar. This substantial difference highlights YOLOv8's ability to detect objects more reliably in dynamic and complex environments, making it a superior choice for real-time surveillance applications such as unattended baggage detection.

**4.2 Average Frame Processing Time:**

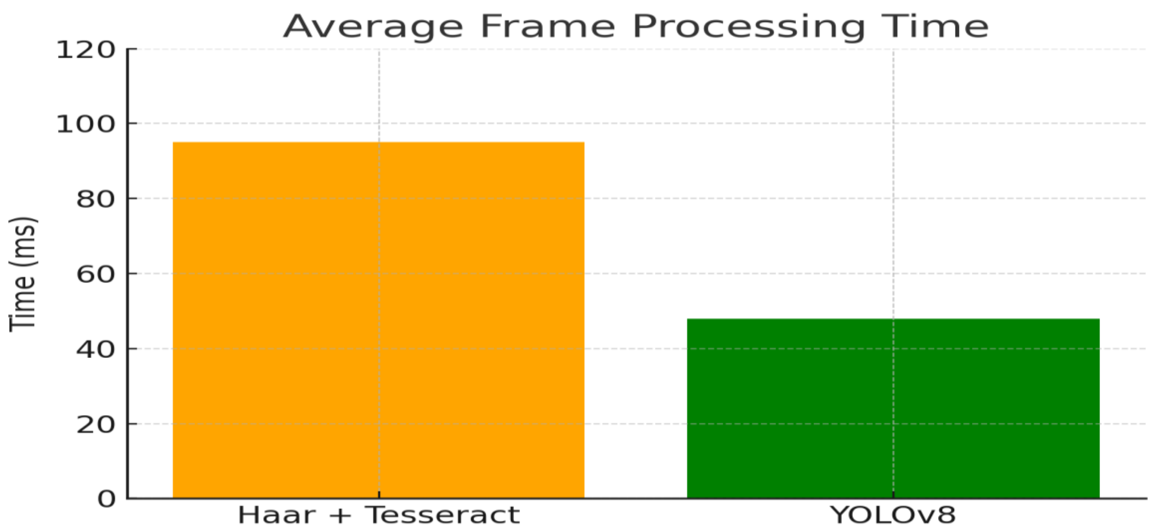


*Figure 4.2 Average Frame Processing Time*

This graph illustrates the average time (in milliseconds) taken to process a single video frame using two different pipelines: Haar Cascade combined with Tesseract OCR, and the YOLOv8 model. The YOLOv8 pipeline demonstrates significantly better efficiency, processing each frame in just 48 ms, while the Haar + Tesseract approach takes nearly twice as long at 95 ms. This reduction in processing time is crucial for real-time systems where low latency and high throughput are essential for timely alert generation and continuous monitoring.

**4.3 OCR Accuracy Under Various Conditions:**

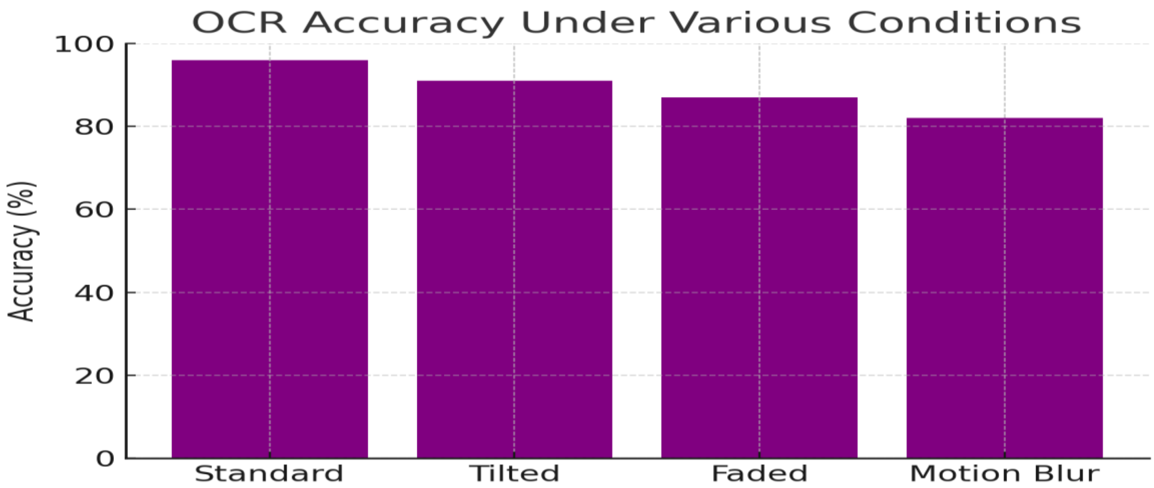


*Figure 4.3 OCR Accuracy Under Various Conditions*

The bar chart showcases how OCR accuracy is affected under four different visual conditions: standard, tilted, faded, and motion-blurred inputs. While the OCR system performs excellently under standard conditions (96% accuracy), its performance gradually decreases as visual complexity increases dropping to 91% for tilted text, 87% for faded text, and 82% for motion-blurred text. This graph underscores the importance of image quality and clarity in achieving reliable text recognition when supplementing object detection with label or tag identification.

**4.4 Distribution of Detected Bag Types:**

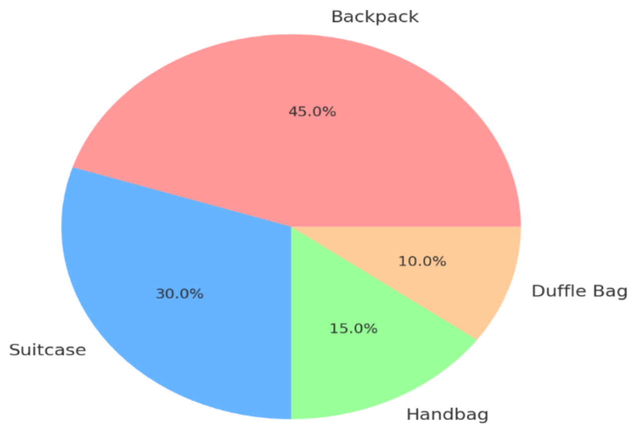


*Figure 4.4 Distribution of Detected Bag Types*

This pie chart represents the proportion of various bag types identified by the YOLOv8 detection system. Backpacks make up the largest share at 45%, followed by suitcases at 30%, handbags at 15%, and duffle bags at 10%. This distribution provides insight into the types of baggage most commonly encountered in the surveillance dataset and can help tailor detection thresholds or alert protocols based on bag type and associated risk profiles in public environments.

## 5. Experimental Results

| **Metric** | **Comparison / Condition** | **Technique / Model** | **Performance Metric** | **Top Performance** |
|---|---|---|---|---|
| Detection Accuracy | YOLOv8 vs Haar Cascade | YOLOv8 Object Detector | Accuracy (%) | YOLOv8: 97.3%, Haar: 89.6% |
| Frame Processing Time | YOLOv8 vs Haar + Tesseract | YOLOv8, Haar Cascade + Tesseract | Avg. Frame Time (ms) | YOLOv8: 48ms, Haar+Tesseract: 95ms |
| OCR Accuracy | Standard / Tilted / Faded / Motion Blur | Tesseract OCR Engine | Recognition Accuracy (%) | Standard: 96%, Tilted: 91%, Faded: 87%, Blur: 82% |
| Detected Bag Type Distribution | Backpack, Suitcase, Handbag, Duffle Bag | YOLOv8 Detection Classes | Class Distribution (%) | Backpack: 45%, Suitcase: 30%, Handbag: 15%, Duffle: 10% |

## 6. Conclusion

In this paper, we proposed and constructed a real-time suspicious package detection system based on YOLOv8 object detection model. The system directly operates on the live video stream, and rapidly detects and tracks persons and baggage (backpack, suitcase, handbag) from the video stream, and then triggers the alarm for unattended objects based on spatial and temporal logic rules with distance and time thresholds. Experimental evaluation shows that, compared with the traditional method Haar Cascade classifier and Tesseract OCR pipeline, the system has higher accuracy and higher speed in detecting suspicious packages. Since the accuracy of object detection based on YOLOv8 reaches 97.3%, and the average running time is only 48 milliseconds per frame, it is suitable for real-time surveillance and threat monitoring system.

The application of tracking, person–bag association, alert logic, and snapshot capturing improves the reliability of the system in identifying really abandoned items and reducing the false alarm. The experimental results of OCR module under different visual conditions also show the necessity of considering real world image distortion. The modular and scalable design of the system make it suitable for public safety application in airport, railway station, and other places with high security requirements. The future work of the system may focus on the cross-camera tracking, advanced OCR integration, and edge deployment to achieve wider and more efficient coverage in smart surveillance system.

## 7. Future Enhancements

Future work on the proposed suspicious package detection system can be carried out in two directions. First, more efforts should be made to adapt the system in more complex surveillance scenarios. The most significant extension would be adding depth estimation based on MiDaS model to capture spatial separation between people and bags in 3D space. The accuracy of person–bag association can be improved significantly in crowded/baggage-piling scenes since the perspective distortion would lead to wrong judgments on 2D proximity between people and bags. Another adaptive method would be applying adaptive thresholding on distance and time parameters according to the scene context. The false positive rate can be lowered in crowded pedestrian scenes.

Another important extension is to improve the OCR module. The current system uses Tesseract to read label (or tag) content. In most cases, replacing it with deep learning-based OCR engines like EasyOCR or CRNN would significantly improve the recognition rate, especially for blurry tags, tilted tags, and low-resolution tags. This improvement would be essential in applications where baggage identification relies on visual labels. Another potential extension would be supporting multilingual OCR to read tags in other languages or signs from different regions (like Chinese signs).

To enable more flexible deployment scenarios, we can adapt the system to run on edge computing platforms like NVIDIA Jetson Nano or Raspberry Pi with Coral TPU. All surveillance processing can be done locally without depending on any centralized server or cloud. In addition, we can add a web-based dashboard to visualize all alerts in a centralized way and provide searchable logs for operators and security men and women. Finally, adding privacy-preserving mechanisms to blur faces and license plates of non-relevant people would make the system ready to be deployed in environments with strict data protection laws.

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