IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Security And Surveillance : Human And Suspicious Object Detection Using Yolo V8

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Abstract: This project presents a real-time surveillance framework designed to detect humans, suspicious objects, and unattended baggage using advanced deep-learning techniques. The system integrates YOLOv8 for object detection along with a custom logic-based behavior engine to identify high-risk scenarios such as abandoned bags, loitering, and restricted area violations. The proposed method enhances the accuracy of automated surveillance by introducing an Owner Association algorithm, which links objects to nearby humans to prevent false alerts. The implementation also includes a Flask-based web interface enabling real-time monitoring, event alerts, and user-defined danger zones. The results demonstrate improved detection reliability, decreased false alarms, and real-time performance suitable for security-critical environments.

***Keywords* -** YOLOv8, Surveillance System, Object Tracking, Unattended Object Detection, Loitering Detection, Flask.

I. Introduction

Modern surveillance systems generate massive volumes of video, making continuous human monitoring impractical. Automated detection systems exist, but most fail to interpret the *context* around detected objects. For example, recognizing a bag is easy but deciding whether the bag is abandoned requires evaluating spatial and temporal behavior. Deep learning based models such as YOLO have significantly improved detection accuracy; however, they lack behavior reasoning. This project bridges that gap by combining YOLOv8's real-time detection capability with a custom-designed logic module capable of analyzing interactions between humans and objects. The framework focuses on detecting critical security scenarios: unattended baggage, people lingering in restricted zones, and line crossing. The project aims to create a low-latency, practical system deployable in public places such as airports, metros, campuses, and event venues.

II. LITERATURE SURVEY

Jocher, Glenn, Ayush Chaurasia, and Jing Qiu (2023) In their work "YOLOv8: Official Documentation and Model Description" the authors introduced architectural upgrades such as an anchor-free detection head and improved feature extraction. They demonstrated that YOLOv8 achieves strong real-time accuracy, making it highly effective for modern surveillance tasks.

Jha, Manoj, and Priyank Verma (2022) Their study "AI-Assisted Detection of Suspicious Objects in Public Surveillance Videos" focused on using deep learning models to identify harmful or unattended objects. They reported significant improvement in detecting suspicious baggage compared to traditional CCTV monitoring.

Zhang, Yifu, Peng Sun, Yu Jiang, and Ze Yuan (2022) In "ByteTrack: Multi-Object Tracking by Associating Every Detection Box", the authors introduced a tracking method that preserves ID stability across frames. The model reduces ID switching, even in dense and occluded scenes, improving long-term tracking accuracy. Their technique strengthens behavior analysis tasks such as loitering, tripwire detection, and owner–object association.

Sharma, Ritesh, and Deepika Chauhan (2021) presented "Deep Learning-Based Loitering Detection in CCTV Surveillance", where the authors demonstrated how dwell-time analysis and movement patterns can be used to identify suspicious behaviour. Their work showed improved accuracy in detecting prolonged presence in restricted zones, highlighting the importance of intelligent behaviour analysis in modern security systems.

III. RESEARCH METHODOLOGY

YOLOv8, an advanced deep-learning model, is the main tool used in building the surveillance system. The development process starts by setting up the required environment and loading the pre-trained model for detecting humans and suspicious objects like backpacks, suitcases and handbags. Once the model is configured, the system is connected with a tracking mechanism to maintain the identity of each detected object across all video frames.

After detection and tracking are confirmed, a custom logic module is created to analyse human–object relationships. This includes identifying which person owns which bag and detecting when a bag becomes unattended. The system also supports additional behaviours such as loitering inside restricted areas and crossing over virtual lines. Each of these activities is monitored using coordinates extracted from detection and tracking outputs.

The system is finally deployed on a web-based platform using Flask. This interface streams real-time video, displays bounding boxes, and shows alerts whenever any suspicious event occurs. The operator can draw restricted zones, set tripwires and adjust detection settings directly from the interface.

The overall procedure is as follows:

1. Install the required Python libraries and set up the YOLOv8 model.
2. Load the dataset or connect to a live webcam/IP camera for video input.
3. Apply YOLOv8 detection to identify humans and suspicious object classes.
4. Integrate a multi-object tracking algorithm (ByteTrack) to assign IDs.
5. Implement the Owner Association logic to link each bag with the nearest person.
6. Continuously check the distance between each person and object to detect unattended bags.
7. Allow the user to draw restricted zones and detect loitering using position tracking.
8. Create a virtual line (tripwire) and count how many people cross it.
9. Use logic skipping to run heavy calculations only every few frames and improve FPS.
10. Deploy the entire system using Flask so the operator can monitor live video and alerts.

For Example: Unattended Bag Detection

- When a bag is detected, its distance to all persons is calculated.
- The nearest person is marked as the owner.
- If the owner walks away and no one is near the bag, a timer starts.
- If the timer exceeds the threshold, the bag is flagged as unattended.

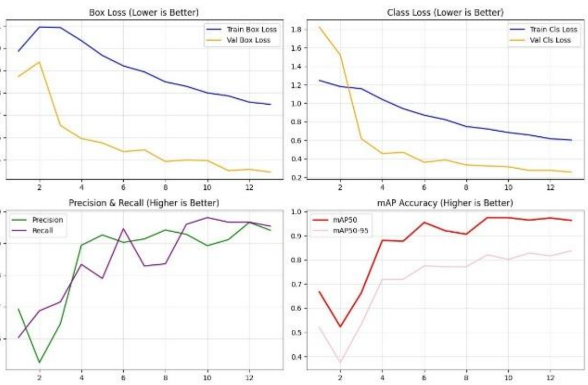

Figure 1: Training and Loss Accuracy

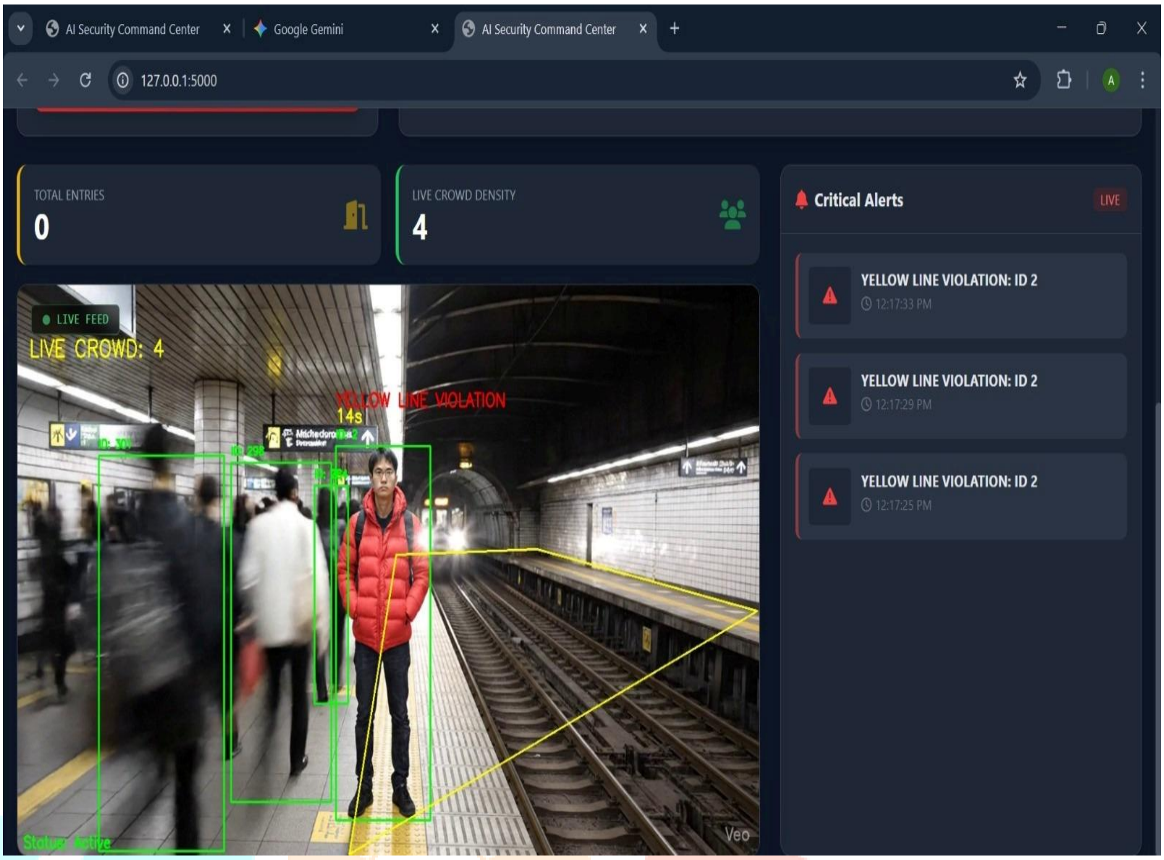

Figure 2: Loitering Detection

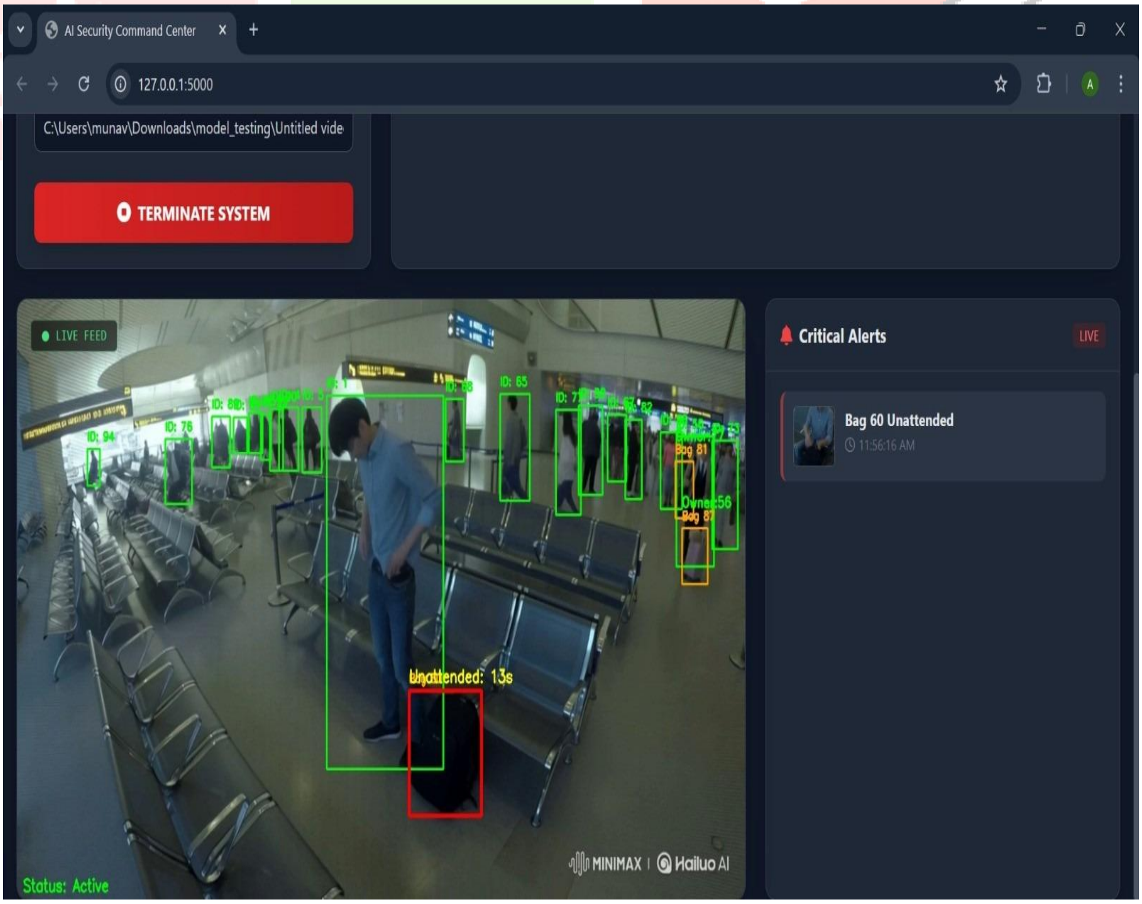

Figure 3: Unattended bag detection in airport

IV. RESULT AND DISCUSSION

1. **Detection Accuracy:** YOLOv8 produced stable and accurate detection of persons and suspicious objects such as backpacks and suitcases under different lighting conditions. Most frames showed consistent confidence scores.
2. **Tracking Performance:** The use of ByteTrack enabled smooth multi-object tracking. Even during short occlusions, IDs were maintained, allowing continuous monitoring of human movement and object association.
3. **Unattended Object Findings:** The Owner Association logic demonstrated reliable results. The system correctly identified the owner of a bag and raised unattended-bag alerts only when the bag was left alone for a set duration.
4. **Loitering Detection:** The restricted-zone feature successfully detected loitering behavior. If a person stayed inside the marked area for longer than the threshold time, an alert was triggered.
5. **Tripwire Monitoring:** The virtual line-crossing system counted entries and exits accurately. It detected direction-based movement and helped in monitoring crowd flow.
6. **System Performance:** Before optimization, the system achieved around 12 FPS. After applying logic skipping, the processing speed increased to nearly 28 FPS, improving real-time usability of the system.
7. **Limitations:** ID-switching occurred when multiple people overlapped, which affected owner tracking for a few seconds. This can be improved by adding ReID models in future versions.

V. CONCLUSION

The implementation of the YOLOv8-based surveillance system provided a clear understanding of how real-time detection and behavioral analysis can improve security monitoring. The experiments showed that human detection, suspicious object identification and movement tracking worked reliably across various situations. The Owner Association logic helped reduce false alarms by correctly identifying when a bag was truly unattended. Loitering and tripwire features added more control, allowing better supervision of restricted areas and movement paths.

Performance improved significantly after applying logic skipping, making the system suitable for continuous live surveillance. Although tracking errors occurred during heavy occlusions, the overall system performance remained stable and effective. These results highlight the usefulness of combining deep-learning detection with rule-based logic for smarter surveillance. The findings support the development of more advanced monitoring systems and encourage future enhancements such as ReID models, pose analysis and deployment on edge devices.

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