

Debris Deputy: A Real-Time AI Surveillance with Database State Tracking System

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Abstract - Improper disposal of waste in public areas is difficult to monitor continuously through conventional surveillance methods, as it requires constant human observation and timely identification of disposal events. This paper presents Debris Deputy: A Real-Time AI-Based Surveillance and Incident Management System developed to identify suspected disposal events from live camera footage. The proposed system uses the You Only Look Once version 8n (YOLOv8n) object-detection model to identify persons and candidate waste objects, while ByteTrack maintains object identities across consecutive video frames. Temporal person-object association is used to determine when an object that was previously associated with a person becomes separated, indicating a suspected disposal event. Upon detection, the system captures an evidence snapshot, performs perceptual hash-based duplicate verification, and stores the incident and its state in MongoDB. A Telegram-based human-in-the-loop mechanism enables monitoring personnel to confirm or reject detected incidents, while a browser-based interface provides access to live surveillance, incident records, notifications, and system statistics. The system integrates detection, tracking, event reasoning, evidence management, database state tracking, and human feedback into a unified surveillance framework for waste-disposal monitoring.

Key Words: Real-Time Surveillance, YOLO, ByteTrack, Waste Disposal Detection, MongoDB.

1. INTRODUCTION

Improper waste disposal is a common problem in public places and has become increasingly difficult to monitor as the amount of waste generated continues to grow. According to the World Bank, approximately 2.56 billion tonnes of municipal waste were generated globally in 2022, and this amount is projected to increase to 3.86 billion tonnes by 2050 if current trends continue [8]. This growing volume highlights the need for effective waste-management and monitoring systems.

Conventional surveillance can record activities, but identifying an actual waste-disposal event often requires continuous human observation.

Recent developments in computer vision and deep learning have made it possible to automate the detection of objects and activities from video footage. However, detecting a waste object in a single frame does not necessarily mean that a person has disposed of it. A person may simply be carrying or interacting with an object. Therefore, a reliable monitoring system needs to consider the relationship between a person and an object across multiple frames and determine whether their interaction changes over time.

This paper presents Debris Deputy: A Real-Time Artificial Intelligence-Based Surveillance and Incident Management System for identifying suspected waste-disposal events. The system uses YOLOv8n for object detection and ByteTrack for tracking persons and objects across consecutive frames [6],[7]. The system analyzes the temporal relationship between the person and the detected waste object to identify a suspected disposal event. Once an event is detected, an evidence snapshot is captured, checked for duplicate incidents, and stored in MongoDB. A Telegram-based notification mechanism allows the monitoring personnel to confirm or reject the detected incident, while a browser-based interface provides access to incident records and monitoring information. The proposed system therefore combines detection, tracking, event analysis, evidence management, database state tracking, and human feedback in a single waste-disposal monitoring framework.

2. LITERATURE SURVEY

Cabungcal et al. [1] proposed a camera-based surveillance system for monitoring violations of garbage disposal schedules. The system integrates YOLO-based object detection to identify persons and garbage from surveillance footage, along with face recognition to identify individuals involved in disposal violations. The detected information, images, and alerts are provided to local authorities for

monitoring and further action. The study also evaluated the system under varying camera distances, viewing angles, and image resolutions, demonstrating the applicability of computer vision for automated garbage-disposal monitoring.

Kumar et al. [2] proposed a vision-based littering detection system using a multi-model computer vision architecture. The approach integrates pose detection, object detection, and face recognition to identify littering activities by analyzing the relationship between a person and the object being handled. The system detects potential littering actions and applies face tagging to associate the detected activity with the corresponding individual. The study reported a precision of 0.947 and recall of 0.857, demonstrating the potential of combining multiple computer vision models for automated littering detection in real-world surveillance environments.

Wibowo et al. [3] investigated deep learning techniques for detecting illegal waste dumps using different YOLO architectures under diverse outdoor conditions. The study compared YOLOv8, YOLOv9, YOLOv10, YOLOv11, and YOLOv12 using an annotated waste-image dataset from urban, coastal, and roadside environments. The models were evaluated using Precision, Recall, F1-Score, mAP@50, and mAP@50-95, with different YOLO versions achieving the best results across these metrics. The study highlights the potential of YOLO-based models for automated illegal waste detection and real-time environmental monitoring.

Rania and Kumar [4] proposed a smart garbage detection system that applies deep learning techniques to automate waste detection and support sustainable waste management. The study focuses on using image-based analysis to identify garbage and reduce the dependence on manual monitoring. The proposed approach demonstrates the application of deep learning and computer vision for detecting waste in real-world environments, providing a basis for automated monitoring and improved waste-management practices. The work highlights the potential of integrating intelligent detection techniques into waste-management systems for more efficient and timely identification of garbage.

Kim and Cho [5] proposed AIDM-Strat, a deep-learning-based system for monitoring illegal waste dumping. The system uses OpenPose to detect a person's wrist position and YOLO to identify garbage bags, determining dumping based on the distance between them. DeepSORT is used to track garbage bags across video frames and reduce false detections. The study reported improved detection performance and fewer false alarms compared with existing behavior-based and zone-based methods.

3. PROPOSED SYSTEM

The proposed system, Debris Deputy, is a real-time AI-based surveillance and incident-management system designed to identify suspected disposal events from continuous camera footage. Unlike a system that only detects the presence of garbage in an image, the proposed system analyzes the interaction between a person and an object over a sequence of video frames. This helps determine whether an object that was previously associated with a person becomes separated from the person, indicating a suspected disposal event.

The system receives live video from a webcam. The incoming video is divided into individual frames and processed using YOLOv8n for detecting persons and candidate objects. ByteTrack is then used to maintain the identity of detected objects across consecutive frames. The tracking information allows the system to observe the movement and relationship between a person and an object over time.

When a person is detected carrying or interacting with an object, the system establishes a temporary association between their tracking IDs. If the previously associated object remains detectable but is no longer spatially associated with the person in a subsequent frame, the system identifies the sequence as a suspected disposal event. An evidence snapshot is then captured from the relevant frame. The snapshot is checked using perceptual hashing to reduce duplicate incident records. Detected non-duplicate incidents are stored in MongoDB along with information such as timestamp, incident ID, object class, event confidence, tracking IDs, image path, and incident status.

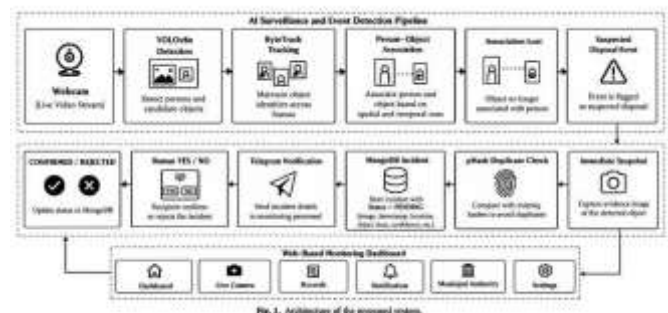


Fig. 1: Architecture of the proposed system.

Fig -1: Architecture of the Proposed System.

4. METHODOLOGY

The proposed Debris Deputy system follows a sequence of stages that process live video, detect and track objects, identify suspected disposal events, and manage the resulting incidents.

4.1 Video Acquisition and Frame Processing

A laptop webcam is used to continuously capture the monitored area. OpenCV processes the video stream frame by frame and forwards the frames to the detection model.

4.2 Object Detection using YOLO

The YOLOv8n object-detection model is used to detect persons and candidate objects in each frame. For every detection, the model provides a class label, bounding box, and confidence value.

The bounding box is represented as:

$$B = (x_1, y_1, x_2, y_2)$$

4.3 Object Tracking using ByteTrack

ByteTrack maintains the identity of detected persons and objects across consecutive frames. Tracking IDs help the system observe the movement of the same person and object over time.

The overlap between two bounding boxes is represented using Intersection over Union (IoU):

$$IoU(B_1, B_2) = \frac{Area(B_1 \cap B_2)}{Area(B_1 \cup B_2)}$$

4.4 Person-Object Association

The system monitors the spatial relationship between a person

and a candidate object. The center of a bounding box is calculated as:

$$C_x = \frac{x_1 + x_2}{2}$$

$$C_y = \frac{y_1 + y_2}{2}$$

This information is used to observe the movement and separation of the person and object.

4.5 Temporal Disposal Event Detection

The system analyzes the person-object relationship across multiple frames. If an object that was previously associated with a person becomes separated from the person, it is identified as a suspected disposal event.

4.6 Event Confidence Calculation

The event confidence is calculated from the detection confidence of the person and object:

$$C_{event} = \frac{C_{person} + C_{object}}{2}$$

The event confidence is an application-level score calculated as the arithmetic mean of the person and object detection confidences, it is not a calibrated probability of disposal.

4.7 Evidence and Duplicate Verification

When a suspected event is detected, an evidence snapshot is captured. Perceptual hashing (pHash) is used to identify visually similar snapshots and reduce duplicate incident records.

The Hamming distance between two hashes is:

$$D_H(H_1, H_2) = \sum_{i=1}^n [H_1(i) \neq H_2(i)]$$

4.8 MongoDB Incident Management

Detected non-duplicate incidents are stored in MongoDB with details such as incident ID, timestamp, evidence image, object class, confidence, tracking IDs, and incident status. The initial status is set to PENDING and is updated after human verification. The database maintains the state of each incident throughout its lifecycle.

4.9 Telegram Notification and Human Verification

The incident evidence and details are sent to authorized monitoring personnel through Telegram. The recipient can confirm or reject the detected incident, after which the incident status is updated in MongoDB.

4.10 Web-Based Monitoring

A Flask-based web interface provides Dashboard, Live Camera, Records, Notification, Municipal Authority, and Settings modules for monitoring incidents, viewing evidence, and managing system configuration.

5. RESULT AND DISCUSSION

The implemented Debris Deputy system was tested using a laptop webcam for real-time monitoring. The obtained results demonstrate the functioning of the object detection, tracking, suspected disposal event detection, incident recording, and human verification modules.

5.1 Real-Time Detection and Tracking:

The live camera module processes the webcam feed and detects persons and candidate objects using YOLOv8n. ByteTrack assigns tracking IDs to the detected objects and maintains their identities across consecutive frames. The system also displays the current event state and event confidence during monitoring.

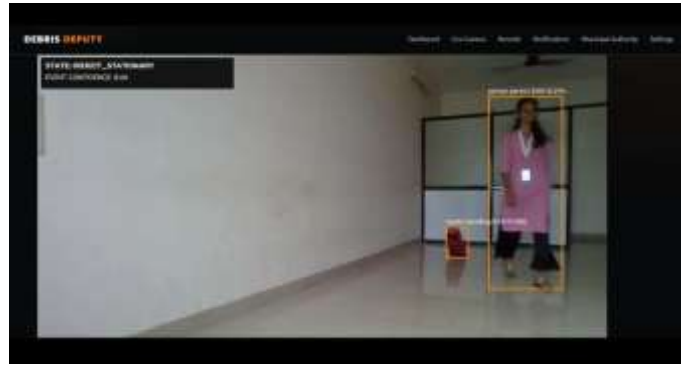


Fig -2: Real-time person and object detection with tracking

5.2 Incident Recording and State Management:

When a suspected disposal event is identified, the system captures an evidence snapshot and creates an incident record. The record contains the detected object, event confidence, tracking IDs, detection time, and incident status. These details are maintained in MongoDB for further monitoring and verification.



Fig -3: Recorded suspected disposal incident

5.3 Human Verification and Notification:

The detected incident is sent to the monitoring personnel through Telegram along with the evidence image and incident details. The notification provides YES and NO options for human verification. The response can then be used to update the corresponding incident status.



Fig -4: The notification contains the detected object, event confidence, evidence snapshot, and human verification options.

The implemented Debris Deputy system was evaluated using a live camera stream, during which two suspected disposal events were successfully recorded. Both events resulted in successful snapshot generation, duplicate verification, MongoDB incident insertion, and Telegram notification, giving a pipeline completion rate of 100%. The mean event confidence was 75.81%, with an average notification latency of approximately 5s and a snapshot resolution of 1280×720 pixels.

Overall, the implemented system provides a complete workflow for monitoring suspected disposal events, from real-time detection and tracking to evidence generation, incident recording, and human verification.

6. FUTURE SCOPE

- **Improved Event Detection:** Advanced temporal and action-recognition techniques can be incorporated to distinguish actual disposal activities from carrying, dropping, or placing objects.
- **Custom Waste Dataset and Model Training:** A project-specific dataset containing diverse waste objects, disposal scenarios, lighting conditions, camera angles, and environments can be used to train and evaluate a dedicated detection model.
- **Advanced Notifications:** Email, SMS, or mobile notifications can be added along with Telegram to provide additional communication channels.
- **Smart Multi-Camera Surveillance:** Multiple cameras can be connected to the system to create a centralized surveillance network covering different locations. Incidents from all cameras can be monitored through a single platform.
- **Smart City Integration:** The system can be integrated with other smart-city platforms and surveillance infrastructure to create a broader automated waste-monitoring network.

7. CONCLUSIONS

The Debris Deputy system demonstrates the application of artificial intelligence and computer vision for real-time monitoring of suspected disposal events. The proposed system combines YOLOv8n object detection, ByteTrack multi-object tracking, person-object association, temporal event analysis, evidence generation, duplicate verification, and MongoDB-based incident state tracking into a unified surveillance framework. Instead of relying only on the presence of a candidate object in an individual frame, the system considers the interaction between a person and an object across consecutive frames to identify a suspected disposal event.

The implemented system successfully generates evidence snapshots and maintains incident information including the detected object, event confidence, tracking IDs, timestamp, and incident status. The integration of Telegram-based human verification provides an additional review stage, while the web-based interface enables centralized monitoring of live video, records, notifications, and system status. The results demonstrate the practical integration of real-time computer vision with database and notification mechanisms for waste-disposal monitoring. Although the system identifies suspected events rather than determining disposal intent with certainty, it

provides a structured foundation for automated surveillance and incident management.

REFERENCES

1. B. G. Cabungcal, N. D. Hidalgo, A. V. U. Lorzano, P. Ona, K. P. Ferraro and A. Santos, "Detection of Violators of Garbage Disposal Schedule with Monitoring System," *TENCON 2024 - 2024 IEEE Region 10 Conference (TENCON)*, Singapore, Singapore, 2024, pp. 1602-1605, doi: 10.1109/TENCON61640.2024.10903035.
2. A. Kumar *et al.*, "Vision Based Littering Detection and Face Tagging using multi-model Architecture," *2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, Greater Noida, India, 2024, pp. 1795-1800, doi: 10.1109/ICACITE60783.2024.10616763.
3. P. Wibowo, A. Z. Wajdi, T. H. Muliawati, A. Fariza and Y. Kiyoki, "Illegal Waste Dump Detection Using a Deep Learning Approach: Performance Evaluation of YOLO Architectures," *2025 International Electronics Symposium (IES)*, Surabaya, Indonesia, 2025, pp. 802-807, doi: 10.1109/IES67184.2025.11161008.
4. Rania and D. Kumar, "Smart Garbage Detection System for Sustainable Waste Management using Deep Learning Techniques," *2024 IEEE International Conference for Women in Innovation, Technology & Entrepreneurship (ICWITE)*, Bangalore, India, 2024, pp. 253-257, doi: 10.1109/ICWITE59797.2024.10503301.
5. Kim, Y.; Cho, J. AIDM-Strat: Augmented Illegal Dumping Monitoring Strategy through Deep Neural Network-Based Spatial Separation Attention of Garbage. *Sensors* 2022, 22, 8819. <https://doi.org/10.3390/s2228819>.
6. Y. Zhang *et al.*, "ByteTrack: Multi-object tracking by associating every detection box," in *Computer Vision – ECCV 2022*, S. Avidan, G. Brostow, M. Cissé, G. M. Farinella, and T. Hassner, Eds., *Lecture Notes in Computer Science*, vol. 13682. Cham, Switzerland: Springer, 2022, pp. 1–21. doi: 10.1007/978-3-031-20047-2_1.
7. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 779–788.
8. E. Cook, K. Ionkova, P. Bhada-Tata, S. Yadav, and F. Van Woerden, *What a Waste 3.0: Global Snapshot of Solid Waste Management Toward Circularity until 2050*. Washington, DC, USA: World Bank, 2026.