Literature Survey (Tabular)

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Author(s)** | **Title** | **Methodology/Approach** | **Dataset/Input Source** | **Imaging Technology** | **Study Area** | **Evaluation Metrics**  **(paper)** | **Key Findings** | **Limitations** | **Our Contribution** | **Our Project Evaluation Metrics** |
| Raza et al., 2021 | Real-Time Trash Detection for Modern Societies Using CCTV | CNN-based object detection | 2,100 annotated CCTV images | Fixed-position CCTV cameras | Urban streets, public bins | mAP ~0.82, Accuracy ~90% | High accuracy for 8 trash categories; effective real-time CCTV detection | Only CCTV-based; no citizen input; no predictive analytics | Added dual data streams (CCTV + citizen uploads), predictive risk heatmaps, real-time auto-tasking | mAP, precision-recall for YOLOv8; cleanup task resolution time; citizen satisfaction score |
| Malik et al., 2023 | Machine Learning-Based  Automatic Litter Detection & Classification in Smart Cities | Transfer learning with CNN (VGG16, ResNet) | Urban litter images (small dataset) | Mobile & handheld cameras | Smart city streets, parks | Accuracy ~93% | Effective multi-category classification | Small dataset; no workflow automation or gamification | Integrated crowdsourced reporting with auto-assignment, gamified citizen engagement | Classification accuracy for uploads; report-to-task latency |
| van Lieshout et al., 2023 | Advancing Deep Learning Detection of Floating Litter | Fine-tuned SqueezeNet, DenseNet | Open water litter dataset | Fixed riverbank cameras | Riverways & coastal areas | Accuracy ~90%, F1 ~0.88 | Robust detection in aquatic environments | Narrow domain; no municipal integration | Applied robust YOLOv8 adaptable to varied urban environments with municipal API integration | Model performance under varied lighting/weather; false positive rate |
| **Pathak et al., 2024** | Smart City Community Watch – Camera-Based Illegal Dumping Detection | DL-based object/event detection | CCTV smart city feeds | High-res public CCTV | Municipal dumping hotspots | mAP ~0.85 | Detects illegal dumping in urban zones | No predictive risk maps or public engagement | Added predictive analytics + gamified leaderboard for proactive cleanliness | Heatmap prediction accuracy; engagement index |
| **Manivannan et al., 2024** | Garbage Monitoring & Management Using DL | UAV imagery, clustering + YOLOv4 detection | UAV municipal zone images | Drone-mounted cameras | Municipal & peri-urban | mAP ~0.845 | Detection + route optimization | Not continuous monitoring; no citizen reporting | Replaced UAV with cost-effective CCTV & mobile app uploads for real-time detection and reporting | Cost per detection; deployment scalability; cleanup proof verification accuracy |
| **Sun et al., 2023** | YOLOv5-OCDS: An Improved Garbage Detection Model | YOLOv5 + ODConv + Soft-NMS + C3DCN | Annotated street garbage images | RGB surveillance cameras | Urban street scenes | mAP@0.5 (95.43%), Recall (91.1%) | High real-time detection performance | Increased model complexity | We apply YOLOv8 with cleaner integration for real-time dashboards and citizen feedback loops | mAP, Precision, Recall, Dashboard response latency, Cleanup verification rate |
| **Gilani et al., 2023** | Skip-YOLO in Multi-Scenes | YOLOv4-tiny + Skip connections | Multi-scene garbage images | Multi-angle camera setup | Urban smart spaces | mAP (88.3%), Precision (85.7%) | Robust in complex object environments | Struggles with novel trash types | We support live citizen image uploads and multi-source input (CCTV + app) | Detection accuracy, Cleanliness score error rate, Heatmap risk prediction accuracy |
| **Cai et al., 2022** | YOLOG: Lightweight Network | Dilated-Deformable CNN + YOLOv4 | Domestic garbage dataset | Edge camera modules (low-power) | IoT/embedded systems | AP@0.5 (94.58%), GFLOPs (6.05) | Lightweight & efficient | Supports only 4 classes | Our system balances lightweight backend with diverse waste classification & location mapping | FPS, Model size vs accuracy trade-off, Post-cleanup verification success rate |
| **Lin et al., 2022** | Soft-YOLOX for Quantity Detection | Soft-NMS + YOLOX | Manhole CCTV feeds | Fixed-angle surveillance cameras | Flood-prone zones | mAP (91.89%), FPS (15.46) | Estimates trash quantity effectively | Static fixed-angle only | We implement zone-wise tracking with cleanup assignment and citizen validation | Cleanup time, Citizen rating match %, Task assignment success rate |
| **Zhou et al., 2024** | EcoDetect-YOLO in Complex Scenes | YOLOv5n + GhostNet + CBAM | Varied lighting, background sets | Outdoor CCTV + adaptive lighting | Mixed public areas | mAP@0.5 (92.14%), F1-score (0.90), FPS (32.9) | Works under difficult lighting conditions | Drop in nighttime accuracy | We include predictive risk analytics using events/footfall + dashboard heatmaps | Predictive risk score accuracy, Daily/Weekly resolution rate, Alert response time |