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DRONE-BASED YOLO MULTI-CLASS TRAFFIC COUNTING ON A ONE-WAY URBAN STREET

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Abstract

This study develops a drone-based multi-class traffic counting system using fine-tuned YOLO11 integrated with the SORT tracking algorithm on a one-way urban corridor. Aerial data was captured at an altitude of 25 meters using a DJI Mavic 3 drone from a nadir perspective to minimize intermodal occlusion. System performance was validated against manual ground truth using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) metrics. The system achieved an overall MAPE of 18% and an RMSE of 45.07. Notably, the car class demonstrated perfect accuracy (0% error), confirming that these automated counts are suitable for direct application in fundamental traffic engineering metrics. Conversely, significant overcounting occurred in the motorcycle class (+34.9%), primarily attributed to Non-Maximum Suppression (NMS) failures under conditions of dense spatial proximity. In civil engineering practice, utilizing uncalibrated automated counts risks overestimating the Volume-to-Capacity (V/C) ratio, leading to a false degradation of the reported Level of Service (LOS). Consequently, a specific calibration factor of -26% for motorcycle counts is essential to ensure data validity for high-precision infrastructure design and signal timing optimization.

Keywords: Drone, Traffic Counting, NMS, SORT, YOLO

Introduction

Urban mobility patterns in many rapidly developing cities continue to evolve, driven by increasing population density and the growing coexistence of vehicles, motorcycles, and pedestrians within constrained public spaces. Real-time monitoring of such multimodal flows has therefore become a critical component of contemporary traffic management, safety assessment, and urban planning. A particularly common element of urban networks especially in dense city centers is the one-way street, which has long been used to streamline circulation and reduce turning conflicts (Gupta et al., 2023, pp. 1–2; Keblawi et al., 2025, pp. 1–3). Recent studies emphasize that the structure of one-way corridors significantly shapes route choice behavior and generates asymmetry between outbound and return travel patterns, illustrating their substantial influence on urban mobility systems (Melo et al., 2022, p. 1; Montello et al., 2023, pp. 1–2). These conditions strain traditional transport systems, prompting an urgent need for real-time observational tools capable of capturing how pedestrians, motorcycles, and vehicles interact within constrained corridors (Chandra et al., 2020, p. 1). The integration of intelligent transport technologies including big-data analytics and AI-enabled sensing has therefore become central to mobility management, as they allow planners and authorities to monitor evolving traffic conditions and respond to operational challenges with greater precision (Montoya-Torres et al., 2021, p. 1; Vyas & Patel, 2024, pp. 1–2). Recent reviews also highlight that advanced monitoring systems are increasingly essential for mitigating congestion, improving safety, and supporting smarter urban mobility strategies as city networks grow more heterogeneous (Butilă & Boboc, 2022, pp. 1–2; Saki & Soori, 2025, pp. 1–2).

One-way streets occupy a distinctive position within urban circulation systems because they reorganize directional movement in ways that can simultaneously enhance traffic efficiency and reshape local mobility behavior (Sun et al., 2022, pp. 1–2; Yulinda et al., 2024, pp. 1–2). Their primary functional appeal lies in the ability to streamline vehicle progression, reduce turning conflicts, and increase effective roadway capacity, particularly in dense districts where physical expansion of street space is no longer feasible (Xu et al., 2021, pp. 1–2; Yan et al., 2024, pp. 1–2). Recent operational studies show that converting selected corridors to one-way flow can relieve segment-level congestion and improve overall network performance when implemented within a coordinated scheme (Rini Nurhasanah & Pamadi, 2024, pp. 657–658; J. Zhang et al., 2020, pp. 1107–1109). Additionally, Alkaissi (2023, pp. 1-6) states that adopting one-way traffic movement promotes the capacity of streets to sustain higher demand and significantly improves traffic operations by reducing control delays at signalized intersections. Similarly, Bindzar et al (2021, pp. 2–3) emphasize that traffic reorganization measures, such as implementing one-way systems around city centers which are often applied to alleviate this problem and reduce traffic pressure on street networks where infrastructure expansion is not feasible.

Advances in surveillance technologies have simultaneously reshaped how complex urban traffic environments are documented and analyzed. The manual traffic-count procedure typically begins with preparing the observation site and the necessary recording sheets. Observers first establish the exact counting point, whether on a roadway segment or at an intersection, and determine the counting interval, which is usually 15 or 60 minutes depending on the study's purpose. Although CCTV networks are widespread in urban areas, aerial observation has gained traction because of its ability to overcome occlusion and limited viewing angles (Pu et al., 2025, pp. 3–4; Sutheerakul et al., 2017, pp. 1718–1720). Promraksa et al (2022, pp. 6–7) show that drones are especially effective in mixed-traffic environments where pedestrians, motorcycles, and other small modes frequently overlap. Drone perspectives offer continuity, enabling researchers to derive behavioral metrics such as evasive maneuvers, lateral clearance, conflict zones, and near-miss events with greater spatial and temporal precision (Barmpounakis et al., 2025, pp. 2–4;Obaid et al., 2025, pp. 1–3).

Computer vision has expanded these observational capabilities by offering scalable tools for automated detection and tracking. The evolution of deep learning-based object detectors can be traced from early convolutional neural networks to the current state-of-the-art You Only Look Once (YOLO) family, which has become the dominant architecture for real-time detection tasks. The YOLO series has progressed through multiple iterations, each addressing limitations of its predecessors: from YOLOv1's pioneering singlse-pass detection to subsequent versions improving accuracy, speed, and multi-scale detection capabilities (Kotthapalli et al., 2025, pp. 1–11). Multi-object tracking algorithms such as Simple Online and Realtime Tracking (SORT) and DeepSORT have been developed to complement detection frameworks by maintaining object identity across frames through Kalman filtering and Hungarian algorithm-based assignment (Farhat et al., 2025, pp. 1–2; Rishika et al., 2023, pp. 255–258). YOLO11, documented and distributed by Ultralytics, represents the latest stage in this trajectory with improvements in backbone and neck design for enhanced feature extraction, optimized training and inference pipelines, and unified support for multiple computer-vision tasks (Huang et al., 2026, pp. 1–2; Khanam & Hussain, 2024, pp. 1–2).

Despite the growing adoption of computer-vision techniques in traffic monitoring, existing studies remain unevenly distributed across road typologies, with most empirical work concentrated on intersections, multi-directional arterials, and vehicular-only scenarios. This imbalance has constrained the generalizability of current findings, as methodological advancements tend to be validated within highly structured environments where traffic movement is predictable and visual occlusions are relatively limited (Bakirci, 2025, pp. 1–2; Chaudhari et al., 2025, pp. 1–3). Recent UAV-based studies demonstrate significant progress in collecting high-resolution visual data for monitoring pedestrian and vehicular flows, yet these contributions still disproportionately emphasize controlled or semi-structured urban settings (Ma et al., 2025, pp. 1–2; Tahir et al., 2024, pp. 1–2). Consequently, the field lacks a sufficiently diverse evidence base to evaluate how computer-vision models perform under heterogeneous traffic compositions typical of one-way urban corridors (Iftikhar et al., 2023, pp. 1–3).

Given these limitations, this study presents a YOLO-based multi-class traffic counting framework tailored to the operational characteristics of one-way urban streets. The specific objectives of this research are: (1) to develop a drone-based multi-class traffic counting system using fine-tuned YOLO11 integrated with the SORT tracking algorithm; (2) to evaluate the accuracy of the automated counting system against manual counting using MAPE and RMSE metrics; and (3) to analyze the main sources of detection errors and identify conditions affecting counting performance. This pilot study focuses on a single one-way corridor in Surabaya, Indonesia, and aims to demonstrate the feasibility of the proposed approach while acknowledging the limitations in generalizability that warrant future multi-site validation.

Research Methods

The study was conducted on a one-way urban arterial corridor at Jalan Jenderal Basuki Rachmad, Surabaya, using a DJI Mavic 3 drone operated at an altitude of 25 meters to capture 4K-resolution video from a nadir perspective. The aerial footage was annotated into four object classes and divided into training, validation, and testing datasets for fine-tuning the YOLO11 model. The trained model was then integrated with the SORT algorithm to enable automated multi-class object detection and tracking. System performance was evaluated by comparing automated counting results with manual observations using Mean Absolute Percentage Error and Root Mean Squared Error metrics.

Research Results and Discussion

This pilot study was conducted along Jalan Jenderal Basuki Rachmad, a one-way urban arterial corridor located in the central business district of Surabaya, East Java, Indonesia. The study segment is classified as an Urban Arterial Road (Class II) according to Indonesian road classification standards, featuring a total carriageway width of approximately 16 meters with four lanes dedicated to motorized traffic flow in a single direction. The traffic flow during the observation period was estimated at approximately 600-800 vehicles per hour equivalent (PCE). Aerial video footage was captured using a DJI Mavic 3 quadcopter drone equipped with a 4/3 CMOS Hasselblad camera capable of recording at 4K resolution (3840 × 2160 pixels) at 30 frames per second. The drone was positioned at a fixed altitude of 25 meters above ground level, providing a nadir (top-down) viewing angle that minimizes perspective distortion and reduces occlusion between adjacent objects. The observation was conducted on a weekend morning (Sunday) at 7:00 AM local time under clear weather conditions with adequate natural lighting.

Each frame was manually annotated using Roboflow platform following the YOLO annotation format. Four object classes were defined: car, motorcycle, bicycle, and person. The annotation strategy followed an instance-level approach where each visible object was annotated independently regardless of spatial relationships (He et al., 2024, pp. 3–5; Nimma et al., 2025; Wang et al., 2024, pp. 4–6). Specifically, when a motorcycle appeared with a rider, two separate bounding boxes were created: one for the motorcycle and one for the person (rider). Similarly, bicycles with cyclists received dual annotations. This annotation strategy was adopted to enable the model to learn individual object features and to support accurate multi-class counting where both vehicles and their operators need to be quantified separately. However, this approach inherently creates overlapping bounding boxes between vehicles and riders, which presents challenges during the Non-Maximum Suppression (NMS) stage as discussed in the results section. The annotated dataset was split into training (80%), validation (10%), and test (10%) subsets using stratified sampling to ensure balanced class representation across splits. Data augmentation techniques including horizontal flipping, brightness adjustment (±15%), and minor rotation (±5°) were applied to the training set to improve model generalization. The complete flow diagram for the fine-tuning process is presented in Figure 1.

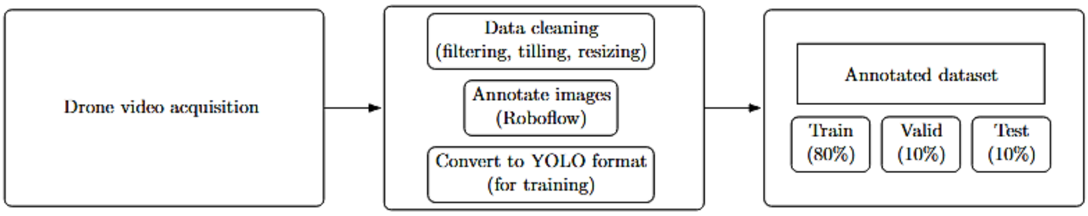

Figure 1. Flow Diagram Fine-Tuning

The training stage of the model produced a series of quantitative performance indicators that summarize its learning behavior and detection capability across the curated dataset. These indicators serve as a basis for evaluating the model's convergence characteristics as well as its suitability for deployment in the subsequent inference phase.

The YOLO11 model, developed and distributed by Ultralytics, was selected as the primary detection backbone due to its improved feature extraction capabilities and optimized inference speed. The model employs a CSPDarknet-based backbone for hierarchical feature extraction, a Path Aggregation Network (PANet) neck for multi-scale feature fusion, and a decoupled detection head that separately processes objectness, classification, and bounding box regression.

The model training was executed on the Google Colab cloud platform, utilizing an NVIDIA A100 Tensor Core GPU (40GB VRAM) to accelerate the fine-tuning process. The training utilized the following hyperparameters: a learning rate of 0.01 with a cosine annealing scheduler, a batch size of 16, an input image resolution of 640×640 pixels, and 100 training epochs. For inference, the confidence threshold was set at 0.25, and the Intersection over Union (IoU) threshold for Non-Maximum Suppression (NMS) was set at 0.45.

The refined model was integrated with the Simple Online and Realtime Tracking (SORT) algorithm to enable multi-object tracking across consecutive frames. SORT employs a Kalman filter for motion prediction and the Hungarian algorithm for detection-to-track association based on IoU overlap. Each detected object is assigned a unique tracking ID that persists across frames, enabling accurate counting when objects cross a predefined counting line. The maximum age parameter for track maintenance was set to 30 frames, allowing temporary occlusions to be handled without creating duplicate counts.

The complete automated counting pipeline is described in Algorithm 1. The process begins with video stream initialization and proceeds through frame-by-frame processing. Each frame undergoes preprocessing (cropping, resizing, and filtering), followed by YOLO11 multi-class object detection. Overlapping detections are merged using NMS, and the SORT tracker updates object trajectories with exponential moving average (EMA) smoothing. Objects crossing the designated counting line are registered with class-specific logic to handle edge cases such as persons riding motorcycles. The algorithm concludes with validation against manual counts using MAPE and RMSE metrics.

Table 1. Algorithm automatic counting

Algorithm multi-object traffic counting using YOLO11 and SORT with validation

```
S ← openStream()                                        ▷ initialize video stream
Tr ←                                                    ▷ initialize tracked objects
Countsauto, Countsmanual ← {}                           ▷ per-frame / per-class counts
for each frame f in S do
    f' ← preprocessF rame(f )                           ▷ crop, resize, filter
    D ← detectObjects(f ')                              ▷ YOLO11 multi-class detection
    for each detection d in D do
        mergeOverlappingDetections(d)
    end for
    Tr ← updateSORT (Tr, D)
    for each tracked object t in T r do                 ▷ SORT tracking (assign IDs)
        smoothTrajectory(t)
        analyseCrossing(t)                              ▷ EMA smoothing of bbox / position
        applyClassLogic(t)                              ▷ gate-line counting, direction checks
    end for                                             ▷ class-specific rules (person on vehicle, etc.)
    Countsauto[frame] ← extractCounts(Tr)
    optionally display annotated frame (f , Tr)         ▷ counts per class for this frame
end for
// — Validation / comparison with manual counting —
Countsmanual ← loadManualCounts(same frames/classes)
E ← []
for each frame i and class c do                         ▷ error list per frame/class
    a ← Countsauto [i,c]
    m ← Countsmanual [i,c]
    e ←|a-m|
    Append E with (i, c, a, m, e)
end for
Compute MAPE: MAPE
Compute RMSE: RMSE
Report table of per-frame/class counts and summary
  statistics (MAPE, RMSE)
```

Model training performance was evaluated using standard object detection metrics: precision, recall, mAP50 (mean Average Precision at IoU threshold 0.50), and mAP50-95 (mean Average Precision averaged across IoU thresholds from 0.50 to 0.95). To establish a reliable ground truth for validation, manual traffic counting was performed by systematically reviewing the exact same recorded drone video footage used for the automated analysis. This approach eliminates temporal discrepancies and ensures a direct, frame-by-frame comparison between the system's output and human observation. The comparison metrics employed were Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), which quantify the magnitude and distribution of counting errors across object classes.

Table 2. Training Performance Model

Class	**Images**	**Instances**	**Precision (%)**	**Recall (%)**	**mAP50 (%)**	**mAP50-95 (%)**
All	98	427	78.4	79.5	81.5	60.5
Bicycle	14	23	60.5	56.5	60.2	38.8
Car	31	37	96	94.6	93.9	90.4
Motorcycle	53	92	76.2	76.5	81.8	47.8
Person	81	275	80.8	90.2	90	65
Speed: 0.5ms, preprocess, 8.8ms inference, 0.0 ms loss, 6.7ms postprocess per image						

From the detailed results presented in Table 2, the all-class performance demonstrates a robust level of detection reliability across the evaluated categories. The Car class exhibits the strongest performance, which aligns with its relatively consistent geometric structure and larger object scale, thereby reducing intra-class ambiguity and supporting higher detection confidence. Although the Person class shows slightly greater visual variability, its high recall indicates that the model effectively identifies pedestrian instances even under fluctuating appearance patterns. In contrast, the comparatively lower mAP50-95 values observed for the Bicycle and Motorcycle classes correspond to well-documented challenges noted in prior studies. Chai et al. (2025, pp. 583–587) emphasize that small targets in complex traffic scenes suffer from weak feature representation, susceptibility to background noise, and scale-related degradation in convolutional layers, resulting in reduced detection accuracy. Similarly, Z. Zhang et al. (2025, pp. 23–25) highlight the difficulty of detecting vulnerable road users including cyclists and micro-mobility users due to inconsistent sizes, dynamic movements, and frequent occlusions in urban traffic environments.

Table 3. Comparison Between Automated and Manual Traffic Counts

Class	**Auto Count**	**Manual Count**	**Absolute Error**	**Percentage Error**	**Error Type**
Bicycle	59	46	13	+28.3%	Overcounting
Car	88	88	0	0.0%	None
Motorcycle	344	255	89	+34.9%	Overcounting
Person	62	68	6	-8.8%	Undercounting
Summary					
MAPE (%)				18%	
RMSE (%)				45.07%	

Table 3 represents the gap between automated counting and manual counting , quantified using MAPE and RMSE, provides a concrete empirical basis for evaluating the system's performance. The numerical discrepancies observed across the four object classes indicate that image-based detection systems do not exhibit uniform performance; rather, their accuracy varies depending on object morphology, movement patterns, and contextual traffic density. The automated system demonstrates minimal deviation for cars, suggesting that larger, structurally consistent objects are detected with high reliability. In contrast, motorcycles and bicycles exhibit greater levels of error due to their smaller size, faster movements, and higher variability in appearance.

The absolute error distribution across classes underscores the importance of class-sensitive calibration in traffic-monitoring deployments. Since motorcycles represent the largest absolute error (89 counts), this class may serve as a focal point for model optimization through adjusting anchor configurations, refining class-specific thresholds, or applying domain-adaptive training strategies.

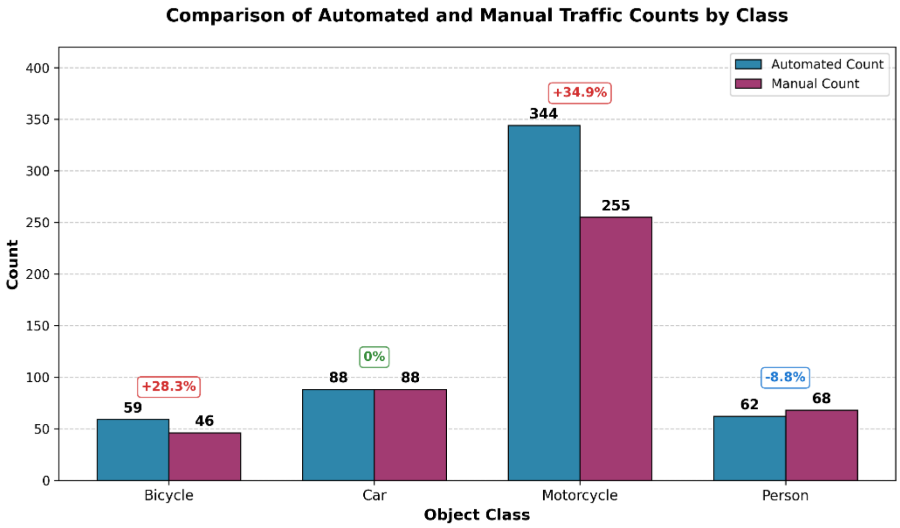

Figure 2. Comparison between Automated and Manual Counts

Figure 2 presents a bar chart comparison between automated and manual counts across the four object classes. The visual representation clearly illustrates the counting accuracy pattern: perfect alignment for cars, slight undercounting for persons, and substantial overcounting for bicycles and motorcycles. The graphical comparison also reveals that the magnitude of overcounting is proportionally larger for motorcycles compared to bicycles, which significantly impacts the overall MAPE and RMSE values.

The MAPE of 18% indicates that the automated counting system produces estimates that deviate, on average, by approximately one-fifth from actual traffic volumes. For traffic planning applications, this level of accuracy is generally acceptable for preliminary assessments, trend analysis, and relative comparisons between time periods or locations. However, for applications requiring high precision such as signal timing optimization or capacity analysis, class-specific calibration factors should be applied: cars require no correction (0% error), pedestrians should be adjusted by approximately +9%, while motorcycles should be corrected by approximately -26% to account for systematic overcounting.

The RMSE of 45.07% reflects the substantial contribution of motorcycle counting errors to overall system performance. Since RMSE penalizes larger errors more heavily, this value indicates that sporadic large discrepancies particularly in motorcycle detection significantly affect aggregate accuracy. For traffic planners working in Southeast Asian urban environments where motorcycles dominate the traffic stream, these correction factors are essential for reliable volume estimation.

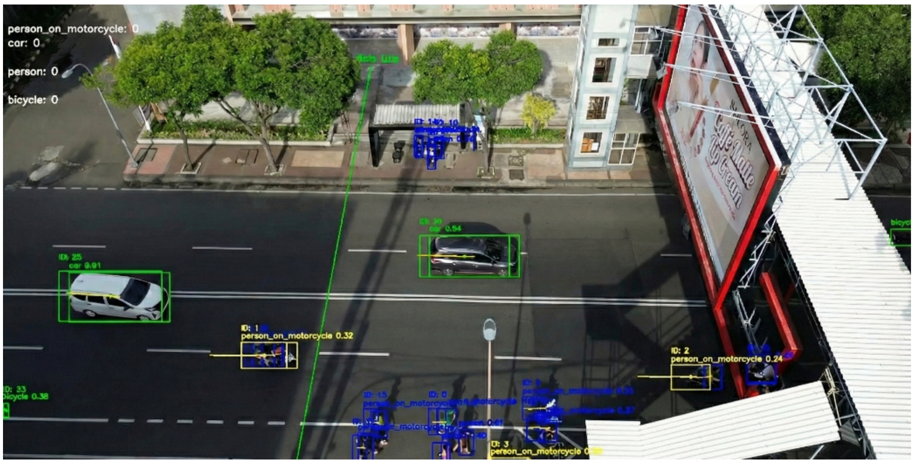

Figure 3. Counting with Yolo Fine-tuned

Figure 3 illustrates the detection and counting results from the fine-tuned YOLO model. A recurring pattern of overcounting for motorcycles and bicycles was observed, particularly when these objects appeared in close spatial proximity to pedestrians.
These discrepancies can be attributed to challenges in the Non-Maximum Suppression (NMS) stage. When bounding boxes of adjacent objects overlap significantly, their high IoU scores may cause detections to be merged or suppressed during post-processing (Bodla et al., 2017, pp. 1–4; Liu et al., 2019, pp. 6459–6461). The fixed IoU threshold in standard NMS struggles to handle the dense, overlapping nature of motorcycle-dominated traffic typical of Southeast Asian urban environments.

To address such limitations, future improvements could incorporate Soft-NMS variants or learned suppression schemes that replace handcrafted heuristics with data-driven approaches (Hosang et al., 2017, pp. 1–7). Such adaptive mechanisms would better preserve detection fidelity in high-density and occlusion-heavy scenes, thereby improving the robustness of the traffic-monitoring model under real-world conditions.

Conclusion

The integration of fine-tuned YOLO11 and the SORT tracking algorithm establishes a functional framework for automated multi-class traffic data extraction on one-way urban corridors. The one-way street environment contributes positively to directional flow stability, which supports consistent automated counting. Quantitative validation against manual ground truth yielded a Mean Absolute Percentage Error (MAPE) of 18% and a Root Mean Squared Error (RMSE) of 45.07%. Notably, the detection for the car class achieved perfect accuracy with a 0% error rate, attributed to its consistent geometric structure and larger object scale. This high level of reliability suggests that the automated counts for cars can be directly utilized for fundamental traffic engineering metrics.

In contrast, significant performance disparities were observed for smaller, high-mobility classes, specifically motorcycles (+34.9% overcounting) and bicycles (+28.3% overcounting). In civil engineering practice, utilizing these uncalibrated automated counts in heterogeneous traffic streams risks overestimating the V/C ratio, which may lead to a false degradation of the reported LOS where a corridor is incorrectly classified as congested. The primary sources of these detection errors were identified as Non-Maximum Suppression (NMS) failures during close-spatial proximity interactions and tracking ID fragmentation. Consequently, while the system is suitable for preliminary volume estimation, a class-specific calibration factor of -26% must be applied to motorcycle counts to ensure data validity for high-precision infrastructure design. Future research should prioritize adaptive NMS variants and multi-scale feature enhancement to improve detection accuracy for small, highly mobile objects.

During the preparation of this work, the author(s) used chatgpt in order to improve readability and language quality. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Alkaissi, Z. A. (2023). The Effect of One-Way Urban Street on Traffic Operation Performance. *E3S Web of Conferences*, *427*. https://doi.org/10.1051/e3sconf/202342703018

Bakirci, M. (2025). Vehicular mobility monitoring using remote sensing and deep learning on a UAV-based mobile computing platform. *Measurement*, *244*, 116579. https://doi.org/10.1016/J.MEASUREMENT.2024.116579

Barmpounakis, M., Espadaler-Clapés, J., Tsitsokas, D., Mordan, T., & Geroliminis, N. (2025). A New Perspective on Urban Mobility Through Large-Scale Drone Experiments for Smarter, Sustainable Cities. *Drones*, *9*(9). https://doi.org/10.3390/drones9090637

Bindzar, P., Saderova, J., Sofranko, M., Kacmary, P., Brodny, J., & Tutak, M. (2021). A case study: Simulation traffic model as a tool to assess one-way vs. two-way traffic on urban roads around the city center. *Applied Sciences (Switzerland)*, *11*(11). https://doi.org/10.3390/app11115018

Bodla, N., Singh, B., Chellappa, R., & Davis, L. S. (2017). Soft-NMS -- Improving Object Detection With One Line of Code. *Proceedings of the IEEE International Conference on Computer Vision*, *2017-October*, 5562–5570. https://doi.org/10.1109/ICCV.2017.593

Butilă, E. V., & Boboc, R. G. (2022). Urban Traffic Monitoring and Analysis Using Unmanned Aerial Vehicles (UAVs): A Systematic Literature Review. In *Remote Sensing* (Vol. 14, Issue 3). MDPI. https://doi.org/10.3390/rs14030620

Chai, X., Zhao, M., Li, J., & Li, J. (2025). Image small target detection in complex traffic scenes based on Yolov8 multiscale feature fusion. *Alexandria Engineering Journal*, *126*, 578–590. https://doi.org/10.1016/J.AEJ.2025.04.105

Chandra, R., Bhattacharya, U., Randhavane, T., Bera, A., & Manocha, D. (2020). *RoadTrack: Realtime Tracking of Road Agents in Dense and Heterogeneous Environments*. http://arxiv.org/abs/1906.10712

Chaudhari, A. A., Treiber, M., & Okhrin, O. (2025). MiTra: A Drone-Based Trajectory Data for an All-Traffic-State Inclusive Freeway with Ramps. *Scientific Data 2025 12:1*, *12*(1), 1174-. https://doi.org/10.1038/s41597-025-05472-0

Farhat, W., Rhaiem, O. Ben, Faiedh, H., & Souani, C. (2025). Pedestrian detection and tracking using an enhanced YOLOv9 model for automotive vehicles. *Measurement*, *254*, 118009. https://doi.org/10.1016/J.MEASUREMENT.2025.118009

Gupta, M., Miglani, H., Deo, P., & Barhatte, A. (2023). Real-time traffic control and monitoring. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *5*. https://doi.org/10.1016/j.prime.2023.100211

He, A., Wu, X., Xu, X., Chen, J., Guo, X., & Xu, S. (2024). Iterative optimization annotation pipeline and ALSS-YOLO-Seg for efficient banana plantation segmentation in UAV imagery. *Frontiers in Plant Science*, *15*, 1508549. https://doi.org/10.3389/FPLS.2024.1508549/BIBTEX

Hosang, J., Benenson, R., & Schiele, B. (2017). Learning non-maximum suppression. *Proceedings -*

30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, *2017-January*, 6469–6477. https://doi.org/10.1109/CVPR.2017.685

Huang, D., Chen, Z., Zhuang, J., Song, G., Huang, H., Li, F., Huang, G., & Liu, C. (2026). DRPU-YOLO11: A Multi-Scale Model for Detecting Rice Panicles in UAV Images with Complex Infield Background. *Agriculture 2026, Vol. 16, Page 234*, *16*(2), 234. https://doi.org/10.3390/AGRICULTURE16020234

Iftikhar, S., Asim, M., Zhang, Z., Muthanna, A., Chen, J., El-Affendi, M., Sedik, A., & Abd El-Latif, A. A. (2023). Target Detection and Recognition for Traffic Congestion in Smart Cities Using Deep Learning-Enabled UAVs: A Review and Analysis. In *Applied Sciences (Switzerland)* (Vol. 13, Issue 6). MDPI. https://doi.org/10.3390/app13063995

Keblawi, M., Maripini, H., Kim, J., Hickman, M., Zheng, Z., & Yildirimoglu, M. (2025). Integrating road network operations planning into real-time traffic management: A conceptual framework. *Transportation Research Interdisciplinary Perspectives*, *32*, 101525. https://doi.org/10.1016/J.TRIP.2025.101525

Khanam, R., & Hussain, M. (2024). *What is YOLOv5: A deep look into the internal features of the popular object detector*. https://arxiv.org/pdf/2407.20892

Kotthapalli, M., Ravipati, D., & Bhatia, R. (2025). *YOLOv1 to YOLOv11: A Comprehensive Survey of Real-Time Object Detection Innovations and Challenges*. https://arxiv.org/pdf/2508.02067

Liu, S., Huang, D., & Wang, Y. (2019). Adaptive NMS: Refining Pedestrian Detection in a Crowd. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2019-June*, 6452–6461. https://doi.org/10.1109/CVPR.2019.00662

Ma, Z., Wang, C., Chen, C., Chen, J., & Zheng, G. (2025). DDF-YOLO: A Small Target Detection Model Using Multi-Scale Dynamic Feature Fusion for UAV Aerial Photography. *Aerospace*, *12*(10). https://doi.org/10.3390/aerospace12100920

Melo, H. P. M., Mota, D. P., Andrade, J. S., & Araújo, N. A. M. (2022). Impact of one-way streets on the asymmetry of the shortest commuting routes. *Physical Review Research*, *4*(2). https://doi.org/10.1103/PhysRevResearch.4.023053

Montello, D. R., Davis, R. C., Johnson, M., & Chrastil, E. R. (2023). The symmetry and asymmetry of pedestrian route choice. *Journal of Environmental Psychology*, *87*, 102004. https://doi.org/10.1016/J.JENVP.2023.102004

Montoya-Torres, J. R., Moreno, S., Guerrero, W. J., & Mejía, G. (2021). Big Data Analytics and Intelligent Transportation Systems. *IFAC-PapersOnLine*, *54*(2), 216–220. https://doi.org/10.1016/j.ifacol.2021.06.025

Nimma, D., Al-Omari, O., Pradhan, R., Ulmas, Z., Krishna, R. V. V., El-Ebiary, T. Y. A. B., & Rao, V. S. (2025). Object detection in real-time video surveillance using attention based transformer-YOLOv8 model. *Alexandria Engineering Journal*, *118*, 482–495. https://doi.org/10.1016/J.AEJ.2025.01.032

Obaid, L., Hamad, K., Al-Ruzouq, R., Dabous, S. A., Ismail, K., & Alotaibi, E. (2025). State-of-the-art review of unmanned aerial vehicles (UAVs) and artificial intelligence (AI) for traffic and safety analyses: Recent progress, applications, challenges, and opportunities. *Transportation Research Interdisciplinary Perspectives*, *33*, 101591. https://doi.org/10.1016/J.TRIP.2025.101591

Promraksa, T., Satiennam, T., Satiennam, W., Kaewwichian, P., & Kronprasert, N. (2022). Factors Influencing Stopping Locations of Motorcycle Riders on Signalized Urban Intersection Approaches. *Sustainability (Switzerland)*, *14*(22). https://doi.org/10.3390/su142215236

Pu, Q., Zhu, Y., Wang, J., Yang, H., Xie, K., & Cui, S. (2025). Drone Data Analytics for Measuring Traffic Metrics at Intersections in High-Density Areas. *Transportation Research Record*, *2679*(5), 361–380. https://doi.org/10.1177/03611981241311566;WEBSITE:WEBSITE:SAGE;JOURNAL:JOURNAL:TRRA;WGROUP:STRING:PUBLICATION

Rini Nurhasanah, & Pamadi, M. (2024). ANALYSIS OF ONE-WAY TRAFFIC REGULATION IN THE MAJALENGKA SQUARE AREA. *LEADER: Civil Engineering and Architecture Journal*, *2*(1), 657–663. https://doi.org/10.37253/leader.v2i1.9530

Rishika, A. L., Aishwarya, C., Sahithi, A., & Premchender, M. (2023). Real-time Vehicle Detection and Tracking using YOLO-based Deep Sort Model: A Computer Vision Application for Traffic Surveillance. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *14*(1), 255–264. https://doi.org/10.17762/TURCOMAT.V14I1.13530

Saki, S., & Soori, M. (2025). Artificial Intelligence, Machine Learning and Deep Learning in Advanced Transportation Systems, A Review. *Multimodal Transportation*, 100242. https://doi.org/10.1016/j.multra.2025.100242

Sun, S., Wang, Y., Yang, L., Wang, Y., Yu, Q., & Liu, Y. (2022). Mining Urban Sustainability: Vehicle Emission Changes on Traffic Corridor by One-Way Traffic Conversion. *Journal of Transportation Engineering, Part A: Systems*, *148*(5), 05022002. https://doi.org/10.1061/JTEPBS.0000662;WGROUP:STRING:PUBLICATION

Sutheerakul, C., Kronprasert, N., Kaewmoracharoen, M., & Pichayapan, P. (2017). Application of Unmanned Aerial Vehicles to Pedestrian Traffic Monitoring and Management for Shopping Streets. *Transportation Research Procedia*, *25*, 1717–1734. https://doi.org/10.1016/j.trpro.2017.05.131

Tahir, N. U. A., Long, Z., Zhang, Z., Asim, M., & ELAffendi, M. (2024). PVswin-YOLOv8s: UAV-Based Pedestrian and Vehicle Detection for Traffic Management in Smart Cities Using Improved YOLOv8. *Drones*, *8*(3). https://doi.org/10.3390/drones8030084

Vyas, A. R., & Patel, P. J. (2024). Real-Time Traffic Surveillance and Vehicle Speed Detection Using Machine Vision ARTICLEINFO ABSTRACT. In *Journal of Information Systems Engineering and Management* (Vol. 2025, Issue 42s). https://www.jisem-journal.com/

Wang, Y., Liu, X., & Wang, R. (2024). Multi-class Object Detection in Urban Scenes Based on Deep Learning. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *10*(3), 417–422. https://doi.org/10.5194/ISPRS-ANNALS-X-3-2024-417-2024

Xu, Q., Chraibi, M., & Seyfried, A. (2021). Anticipation in a velocity-based model for pedestrian dynamics. *Transportation Research Part C: Emerging Technologies*, *133*, 103464. https://doi.org/10.1016/J.TRC.2021.103464

Yan, X., He, J., Wu, G., Sun, S., Wang, C., Fang, Z., & Zhang, C. (2024). Driving risk identification of urban arterial and collector roads based on multi-scale data. *Accident Analysis & Prevention*, *206*, 107712. https://doi.org/10.1016/J.AAP.2024.107712

Yulinda, M., Putri, E., Siahaan, L. D., & Suryobuwono, A. A. (2024). A Study of One-Way Road Implementation To Improve Performance In The City of Pagar Alam. *Dinasti International Journal of Digital Business Management*, *5*(5), 981–988. https://doi.org/10.38035/DIJDBM.V5I5.3219

Zhang, J., Zhang, X., Yang, Y., & Zhou, B. (2020). Study on the influence of one-way street optimization design on traffic operation system. *Measurement and Control (United Kingdom)*, *53*(7–8), 1107–1115. https://doi.org/10.1177/0020294020932366

Zhang, Z., Wei, C., Wu, G., & Barth, M. J. (2025). Vulnerable Road User Detection for Roadside-Assisted Safety Protection: A Comprehensive Survey. In *Applied Sciences (Switzerland)* (Vol. 15, Issue 7). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/app15073797