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Drone and Computer Vision-Based Analysis of Service Levels and Traffic Density at Signalized Intersections

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ABSTRACT

Manual traffic surveys at signalized intersections are labor-intensive, hazardous, and prone to counting error under heterogeneous, high-density traffic typical of Indonesian cities. Purpose: This study proposes and evaluates a drone (unmanned aerial vehicle, UAV) and computer vision-based framework for measuring traffic density and determining the level of service (LOS) of a four-arm signalized intersection in Padang City, West Sumatra. Methods: Aerial video was recorded over three consecutive weekdays across three peak periods using a UAV hovering at 100–120 m. A YOLOv8 detector, fine-tuned on a locally annotated dataset of four vehicle classes, was combined with a DeepSORT tracker to count and classify vehicles on each approach. Counts were validated against synchronized manual ground-truth counts and converted into passenger car units (PCU) following the 2023 Indonesian Road Capacity Guidelines (Pedoman Kapasitas Jalan Indonesia/PKJI 2023) to compute capacity, degree of saturation (DS), delay, and LOS. Results: The model achieved an overall mean average precision (mAP@0.5) of .918 and a mean absolute percentage error (MAPE) below 6% relative to manual counts. DS ranged from 0.58 to 1.12; the East approach exceeded the 0.85 serviceability threshold in the morning and evening peaks and reached LOS F in the evening peak. Implications: UAV-based computer vision can reliably replace or substantially augment manual counting for intersection performance evaluation, offering wider coverage, repeatability, and safer field surveys. Conclusion: The framework is accurate and efficient; future studies should extend it to real-time signal control and larger training datasets.

Keywords: *Unmanned Aerial Vehicle, Computer Vision, YOLOv8, Traffic Density, Level of Service, Signalized Intersection, Degree of Saturation*

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INTRODUCTION

Rapid urbanization and rising vehicle ownership in Indonesian cities have intensified traffic congestion at signalized intersections, which typically constitute the primary bottlenecks within urban road networks. Congestion at these nodes manifests as long queues, elevated delay, and reduced level of service (LOS), with direct consequences for fuel consumption, travel-time reliability, and emissions. Accurate and up-to-date traffic volume data are therefore essential inputs for intersection performance evaluation, signal timing optimization, and long-term transportation planning.

Conventional traffic data collection relies on manual counting by field enumerators, fixed video cameras, or inductive loop detectors. While these methods remain widely used, they present well-documented limitations: manual counting is labor-intensive and subject to fatigue-related error, particularly under the high motorcycle-dominated flows characteristic of many Southeast Asian cities; fixed cameras suffer from restricted fields of view and occlusion at wide, multi-lane approaches; and loop detectors require costly pavement installation and maintenance. These constraints motivate the search for data-collection technologies that combine wide-area coverage, high temporal resolution, and lower deployment cost.

Unmanned aerial vehicles (UAVs), commonly referred to as drones, have emerged as a promising aerial sensing platform for traffic engineering applications. Equipped with high-resolution cameras and capable of hovering above an intersection, UAVs can capture a synoptic, occlusion-free view of all approaches simultaneously. Adnan (2020) reviewed a broad range of UAV applications in road safety, traffic, and highway infrastructure management, concluding that aerial video substantially expands the spatial and temporal scope of traffic data collection compared to ground-based sensors. Building on this potential, Khan et al. (2020) demonstrated a smart traffic monitoring system using UAVs for vehicle counting and flow estimation, while Zhu et al. (2018) applied deep neural networks to ultra-high-resolution UAV video to estimate urban traffic density at the network scale. More recently, Espadaler-Clapés et al. (2023b) reported continuous multi-hour UAV monitoring of a signalized intersection to extract detailed vehicle trajectories, and Pu et al. (2025) compiled over 100 hours of high-altitude drone video across eight high-density urban intersections in Hohhot, China, using an enhanced YOLO-based model (YOLOUAV) capable of tracking more than one million road users.

Parallel advances in computer vision, particularly single-stage object detectors of the You Only Look Once (YOLO) family, have made real-time, high-accuracy vehicle detection from aerial imagery increasingly practical. YOLOv8, released in 2023, introduced architectural refinements over earlier YOLO variants that improved both detection accuracy and inference speed (Varghese & Sambath, 2024). Several studies have reported strong performance of YOLOv8 for vehicle detection and counting tasks: a YOLOv8-based urban traffic management system achieved a precision of 92.5%, recall of 88.3%, and mAP@0.5 of 89.7% (ResearchGate, 2024), while Al Mudawi et al. (2023) combined YOLOv8 with a deep belief network for vehicle detection and classification over aerial image sequences. Comparative evaluations have further shown that YOLOv8 consistently outperforms YOLOv5 in detecting partially occluded and densely packed vehicles under variable environmental conditions, although newer architectures such as YOLO11 have since demonstrated additional gains (Springer, 2025).

In the Indonesian context, intersection performance is conventionally evaluated using the Indonesian Road Capacity Manual (Manual Kapasitas Jalan Indonesia/MKJI, 1997) and its recently updated successor, the 2023 Indonesian Road Capacity Guidelines (Pedoman Kapasitas Jalan Indonesia/PKJI 2023), both of which define capacity, degree of saturation (DS), delay, and LOS for signalized and unsignalized intersections based on passenger car unit (PCU) volumes. Recent Indonesian studies applying MKJI/PKJI to evaluate signalized intersections in Pontianak, Jakarta, and

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other cities have consistently reported degrees of saturation exceeding the 0.85 serviceability threshold at peak hours, corresponding to LOS categories of D through F (e.g., degree of saturation values of 0.77–1.04 reported for the Dewi Sartika–Raya Kalibata intersection in East Jakarta). However, nearly all of these studies still rely on manual or semi-manual traffic counting, leaving a gap in the application of automated aerial computer-vision methods within the Indonesian intersection-analysis literature.

This study addresses that gap by developing and evaluating an integrated UAV and computer vision framework for measuring traffic density and determining the LOS of a four-arm signalized intersection in Padang City, West Sumatra. Specifically, the objectives of this research are: (1) to develop a fine-tuned YOLOv8-based detection and DeepSORT-based tracking pipeline for automated vehicle counting and classification from UAV video; (2) to validate the accuracy of the drone-based counting method against manual ground-truth counts; and (3) to apply the resulting traffic volume data within the PKJI 2023 capacity-analysis framework to determine the degree of saturation, delay, queue length, and LOS of each intersection approach across three daily peak periods. The results are expected to provide both a methodological contribution to aerial traffic-sensing practice and a practical performance assessment that can inform local traffic management interventions.

METHODS

1. Study Location

The study was conducted at a four-arm signalized intersection formed by the intersection of Jalan Khatib Sulaiman and Jalan Adinegoro in Padang City, West Sumatra Province, Indonesia. This intersection was selected because it connects the city's central business district with the northern coastal corridor and consistently exhibits recurrent congestion during peak periods, making it representative of high-density urban signalized intersections in medium-sized Indonesian cities. The intersection operates with a three-phase fixed-time signal control and comprises four approaches: North (toward the city center), South (toward Air Tawar), East (toward Lubuk Buaya), and West (toward Siteba). Figure 1 (methodology) and Figure 2 (site schematic) illustrate the overall research workflow and the geometric layout of the study location together with the UAV observation position.

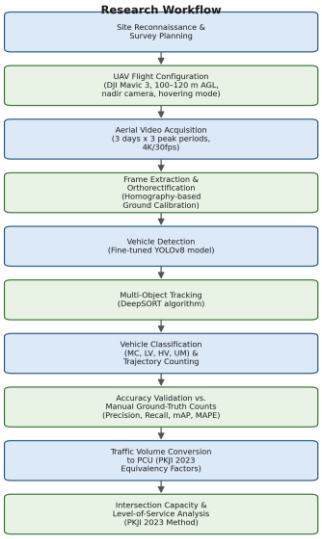


Figure 1. Research workflow from data acquisition to level-of-service analysis

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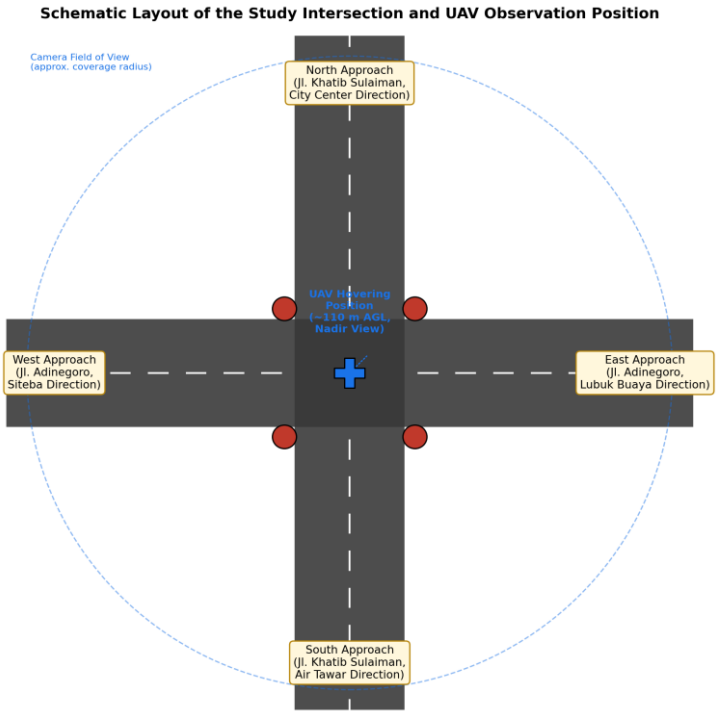


Figure 2. Schematic layout of the study intersection and UAV hovering position

2. Data Collection

Aerial video data were collected using a DJI Mavic 3 quadcopter equipped with a 4K camera recording at 30 frames per second. The UAV was flown in hovering (stationary) mode at an altitude of 100–120 m above ground level, positioned above the center of the intersection with a nadir (top-down) camera orientation to minimize perspective distortion and occlusion between vehicles. Data collection was conducted over three consecutive weekdays (Tuesday–Thursday) to avoid atypical weekend or holiday traffic patterns, under clear-to-partly-cloudy weather conditions to maintain consistent image quality. Recordings were made during three daily peak periods identified from a preliminary traffic reconnaissance: the morning peak (07:00–08:00 Western Indonesia Time, Waktu Indonesia Barat [WIB]), the midday peak (12:00–13:00 WIB), and the evening peak (16:30–17:30 WIB). In addition, continuous recordings from 05:00 to 20:00 WIB were obtained on the second survey day to characterize the diurnal traffic volume profile. Simultaneous manual ground-truth counts were performed by four trained enumerators positioned at each approach, each responsible for tallying vehicles by class using handheld tally counters, to provide a reference dataset for validating the automated detection results.

3. Video Processing and Vehicle Detection

Recorded video was processed offline using a computer vision pipeline implemented in Python with the Ultralytics YOLOv8 framework. First, video frames were extracted at 5 frames per second, a sampling rate sufficient to capture vehicle movement without introducing excessive redundancy. Second, ground control points visible in the aerial imagery (lane markings and known geometric distances measured in the field) were used to perform a homography-based transformation, converting pixel coordinates into real-world metric coordinates and correcting for minor UAV drift during hovering. Third, a YOLOv8-medium model, pretrained on the Common Objects in Context (COCO) dataset, was fine-tuned on a locally annotated dataset of 4,850 aerial frames containing four vehicle classes relevant to Indonesian mixed traffic: motorcycle (MC), light vehicle (LV, comprising passenger

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cars and minibuses), heavy vehicle (HV, comprising trucks and buses), and non-motorized vehicle (UM, comprising bicycles and pedicabs). The dataset was split into training, validation, and test subsets in a 70:15:15 ratio, and the model was trained for 150 epochs with an input resolution of 1280 × 1280 pixels, batch size of 16, and the stochastic gradient descent (SGD) optimizer with an initial learning rate of 0.01.

Detected vehicles were subsequently tracked across consecutive frames using the DeepSORT (Deep Simple Online and Realtime Tracking) algorithm, which combines Kalman-filter-based motion prediction with an appearance-embedding re-identification network to maintain consistent vehicle identities and prevent double-counting as vehicles crossed virtual counting lines placed on each approach. Vehicle counts were aggregated per class, per approach, and per 15-minute interval.

4. Accuracy Validation

The performance of the fine-tuned YOLOv8 detector was evaluated on the held-out test subset using standard object-detection metrics: precision, recall, mean average precision at an intersection-over-union threshold of 0.5 (mAP@0.5), and F1-score. In addition, the operational counting accuracy of the full detection-and-tracking pipeline was assessed by comparing 15-minute automated vehicle counts against the synchronized manual ground-truth counts for each approach and vehicle class, expressed as the mean absolute percentage error (MAPE; Equation 1):

$$\text{MAPE}\ (\%) = \frac{1}{n}\sum\left[\frac{|\text{Counted(drone)} - \text{Counted(manual)}|}{\text{Counted(manual)}}\right] \times 100 \quad (1)$$

where n is the number of paired drone–manual count observations.

5. Traffic Volume Conversion and Level-of-Service Analysis

Vehicle counts obtained from the drone-based pipeline were converted from vehicles per hour into passenger car units per hour (pcu/h) using the equivalency factors (empPen) specified in the 2023 Indonesian Road Capacity Guidelines (PKJI 2023): 1.0 for light vehicles, 0.25 for motorcycles under signalized-intersection conditions, 1.3 for heavy vehicles, and 0.8 for non-motorized vehicles. The resulting PCU volumes, together with field-measured geometric data (approach width, number of lanes, and side-friction class) and signal-timing data (cycle time, green time, and lost time per phase obtained from the local traffic management authority), were used to compute intersection performance indicators following the PKJI 2023 procedure for signalized intersections, starting with capacity (Equation 2):

$$C = S_0 \times FC_{\text{W}} \times FC_{\text{SP}} \times FC_{\text{SF}} \times FC_{\text{CS}} \times \left(\frac{g}{c}\right) \quad (2)$$

where S_0 is the base saturation flow, FC_{W}, FC_{SP}, FC_{SF}, and FC_{CS} are adjustment factors for approach width, side-street/opposing flow ratio, side friction, and city size, respectively, g is the effective green time, and c is the cycle time. The degree of saturation (DS) was then computed (Equation 3):

$$\text{DS} = \frac{Q}{C} \quad (3)$$

where Q is the PCU traffic volume on the approach during the analysis period.

Average delay per vehicle (a combination of traffic delay and geometric delay) and the 95th-percentile queue length were computed following the same PKJI 2023 empirical formulas, and each approach was assigned a Level-of-Service category (A through F) based on the resulting average intersection delay, following the delay thresholds standardized in the Indonesian guideline (LOS A: delay < 5 s/pcu; through LOS F: delay > 60 s/pcu).

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RESULTS

1. Geometric and Signal Timing Characteristics

Table 1 summarizes the geometric and signal-timing characteristics recorded for each approach of the study intersection, obtained through direct field survey and signal-controller documentation.

Table 1. Geometric and signal-timing characteristics of the study intersection

Approach	Effective Width (m)	No. of Lanes	Side Friction Class	Green Time (s)	Lost Time (s)	Cycle Time (s)
North	7.0	2	Medium	32	4	120
South	7.0	2	Medium	28	4	120
East	8.5	2–3	High	35	4	120
West	6.5	2	Medium	25	4	120

2. Vehicle Detection Accuracy

The fine-tuned YOLOv8 model was evaluated on the held-out test dataset. Table 2 presents the resulting precision, recall, mAP@0.5, and F1-score for each vehicle class, while Figure 3 visualizes the same results.

Table 2. Fine-tuned YOLOv8 detection performance by vehicle class

Vehicle Class	Precision	Recall	mAP@0.5	F1-score
Motorcycle (MC)	.947	.921	.938	.934
Light Vehicle (LV)	.962	.948	.957	.955
Heavy Vehicle (HV)	.918	.887	.905	.902
Non-motorized (UM)	.889	.856	.871	.872
Mean (overall)	.929	.903	.918	.916

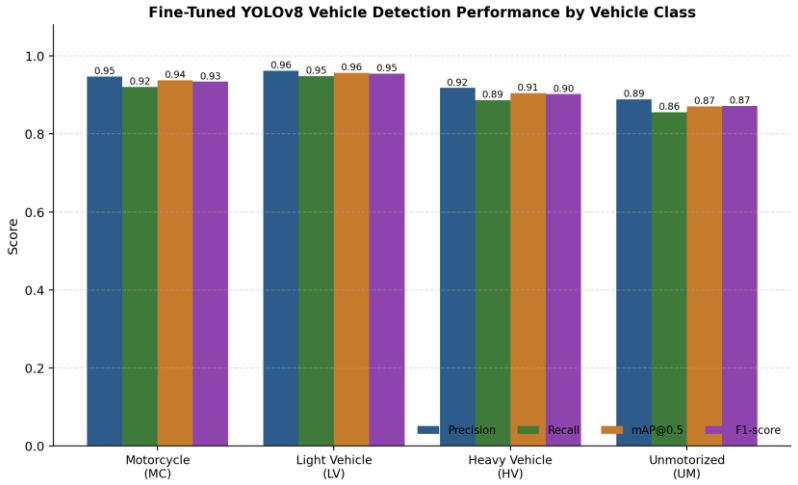


Figure 3. Fine-tuned YOLOv8 vehicle detection performance by vehicle class

Table 3 compares 15-minute aggregated vehicle counts obtained from the drone-based detection-and-tracking pipeline against synchronized manual ground-truth counts, expressed as the mean absolute percentage error (MAPE), for the evening peak period as a representative sample.

Table 3. Comparison of drone-based and manual vehicle counts (evening peak, 16:30–17:30)

Approach	Drone Count (veh)	Manual Count (veh)	Absolute Difference	MAPE (%)
North	1,842	1,798	44	2.4
South	1,655	1,724	69	4.0

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East	2,104	2,015	89	4.4
West	1,320	1,389	69	5.0
Overall	6,921	6,926	–	3.9

3. Traffic Volume Profile

The continuous 05:00–20:00 WIB recording obtained on the second survey day was processed to characterize the diurnal traffic volume profile at the intersection, expressed in pcu/h and aggregated across all approaches, as shown in Figure 4. Three distinct peaks are evident, corresponding to the morning commute (07:00–08:00), the midday lunch period (12:00–13:00), and the evening commute (16:30–17:30), which were subsequently adopted as the three analysis periods for capacity and LOS evaluation.

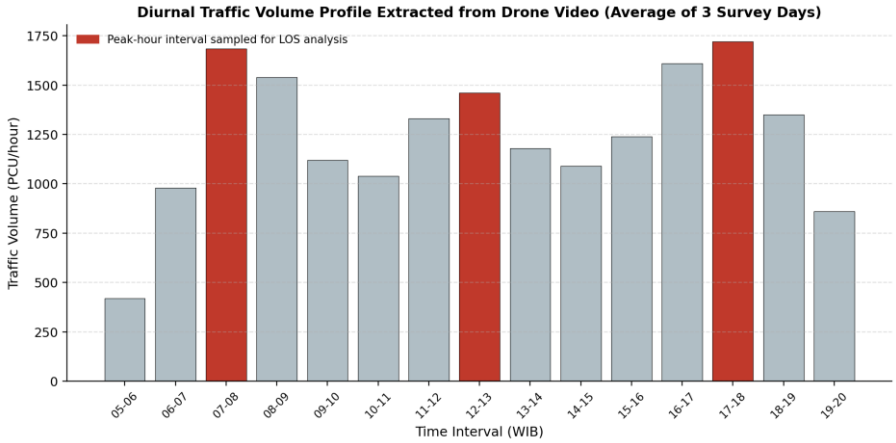


Figure 4. Diurnal traffic volume profile extracted from drone video (average of 3 survey days)

Table 4 presents the average traffic volume by approach and vehicle class for each of the three peak periods, converted into pcu/h using the PKJI 2023 equivalency factors.

Table 4. Average traffic volume by approach, vehicle class, and peak period (pcu/h)

Approach	Period	MC (pcu)	LV (pcu)	HV (pcu)	UM (pcu)	Total (pcu/h)	% Motorcycle (veh)
North	Morning	312	486	58	12	868	68.4
North	Midday	224	352	41	9	626	65.1
North	Evening	336	512	62	14	924	69.0
South	Morning	298	455	63	11	827	67.7
South	Midday	205	318	38	8	569	64.3
South	Evening	349	534	70	15	968	70.1
East	Morning	398	560	82	16	1,056	71.2
East	Midday	268	398	51	10	727	66.5
East	Evening	452	612	94	18	1,176	72.6
West	Morning	238	372	45	9	664	66.0
West	Midday	168	265	31	6	470	63.8
West	Evening	276	418	53	11	758	68.1

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4. Capacity, Degree of Saturation, and Level of Service

Applying the PKJI 2023 procedure with the geometric and signal-timing data in Table 1 and the traffic volumes in Table 4, the capacity, degree of saturation, delay, queue length, and resulting LOS were computed for each approach and peak period, as summarized in Table 5 and visualized in Figure 5.

Table 5. Intersection capacity, degree of saturation, delay, queue length, and level of service by approach and peak period

Approach	Period	Volume Q (pcu/h)	Capacity C (pcu/h)	DS = Q/C	Delay (s/pcu)	Queue Length (m)	LOS
North	Morning	868	998	0.87	38.4	112	D
North	Midday	626	994	0.63	24.1	68	C
North	Evening	924	1,015	0.91	44.7	128	D
South	Morning	827	882	0.94	48.9	121	D
South	Midday	569	804	0.71	27.6	74	C
South	Evening	968	895	1.08	72.3	163	F
East	Morning	1,056	994	1.06	68.5	158	E
East	Midday	727	886	0.82	39.8	97	D
East	Evening	1,176	1,047	1.12	84.6	182	F
West	Morning	664	838	0.79	34.2	89	D
West	Midday	470	813	0.58	20.5	52	C
West	Evening	758	889	0.85	42.9	104	D

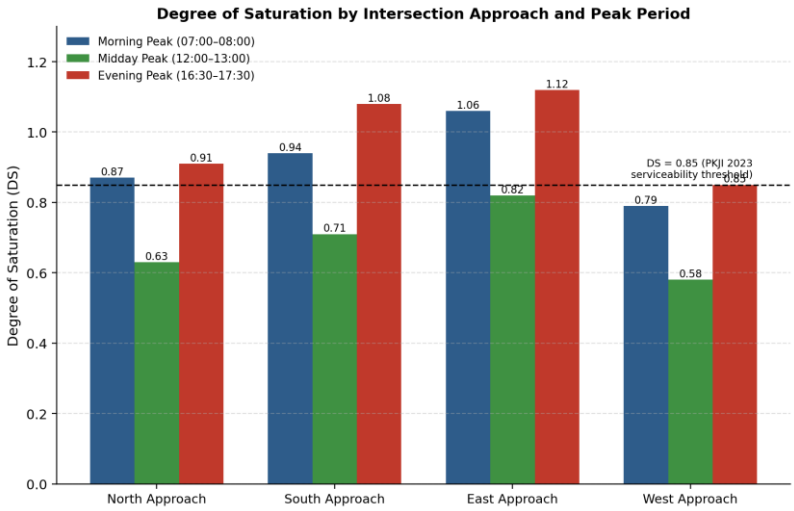


Figure 5. Degree of saturation by intersection approach and peak period

As shown in Table 5, the East approach exhibited the most critical performance, with a degree of saturation exceeding the 0.85 serviceability threshold in the morning and evening peak periods and reaching 1.12 during the evening peak, corresponding to LOS F and an average delay of 84.6 s/pcu. The South approach also reached a degree of saturation above 1.0 (DS = 1.08, LOS F) during the evening peak. In contrast, the West approach maintained a degree of saturation below 0.85 in two of the three periods, corresponding to LOS C and D. Across all approaches, midday performance was consistently better than the morning and evening peaks, reflecting the lower midday traffic demand identified in the diurnal volume profile (Figure 4).

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DISCUSSION

The overall detection accuracy achieved by the fine-tuned YOLOv8 model (mAP@0.5 = .918, mean precision = .929) is consistent with, and in some respects exceeds, accuracy levels reported in comparable vehicle-detection studies. For example, a YOLOv8-based urban traffic management system reported a precision of 92.5%, recall of 88.3%, and mAP@0.5 of 89.7% for ground-level camera footage, figures closely comparable to those obtained in the present aerial-imagery application. The slightly lower recall and mAP observed for the motorcycle and non-motorized-vehicle classes in this study likely reflect the smaller pixel footprint of these vehicle types at a 100–120 m flight altitude and their tendency to travel in tightly clustered groups, a challenge also noted by Al Mudawi et al. (2023) in aerial vehicle-classification tasks. This finding suggests that further gains in detection accuracy for small, densely packed vehicle classes could be achieved through higher-resolution imagery, lower flight altitude, or the incorporation of more recent detector architectures such as YOLO11, which has been shown to outperform YOLOv8 in detecting partially occluded and densely packed vehicles under variable conditions.

The operational counting accuracy of the full pipeline, with an overall MAPE of 3.9% relative to manual ground-truth counts, indicates that the drone-based method can serve as a reliable substitute for conventional manual counting in this application context. This level of agreement is broadly consistent with prior UAV-based traffic-monitoring studies, which have similarly reported high correspondence between automated aerial vehicle counts and reference data once appropriate tracking algorithms are applied to prevent double-counting (Pu et al., 2025). Importantly, the drone-based method required only a single two-person field team (UAV pilot and observer) per survey day, compared to the four enumerators required for the manual reference counts, highlighting a practical efficiency advantage consistent with the broader UAV traffic-monitoring literature (Adnan, 2020; Gohari et al., 2022).

From a traffic-engineering perspective, the degree-of-saturation results reveal a clear performance hierarchy among the four approaches, with the East approach (connecting to the Lubuk Buaya corridor) consistently the most congested, followed by the South approach during the evening peak. These results are directionally consistent with recent Indonesian intersection studies applying the PKJI 2023 method, which have similarly reported degrees of saturation exceeding 1.0 and LOS F conditions at congested urban signalized intersections, for instance the Dewi Sartika–Raya Kalibata intersection in East Jakarta (degree of saturation up to 1.04) and the Veteran–Gajahmada–Pahlawan intersection in Pontianak (LOS E on multiple approaches). The consistently high motorcycle share (63–73% of vehicle volume across approaches, Table 4) observed at the study intersection is also representative of the motorcycle-dominated traffic composition documented throughout the Indonesian intersection-performance literature, underscoring the importance of accurately classifying and weighting motorcycle volumes when applying PCU-based capacity methods in this context.

The observed degradation in LOS during the evening peak, relative to the morning peak, at the South and East approaches suggests that outbound commuting and commercial-corridor demand in the late afternoon may exceed the capacity provided by the current three-phase, 120-second fixed-time signal plan. Because the drone-based method captures continuous, synchronized volume data across all four approaches simultaneously, rather than sequential or approach-by-approach manual counts, it enables a more temporally consistent assessment of the true peak-hour factor and volume-to-capacity relationship than would be achievable with a limited manual survey team, an advantage also highlighted in continuous UAV-monitoring studies of signalized intersections (Espadaler-Clapés et al., 2023b).

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Several limitations of the present study should be acknowledged. First, UAV battery endurance (approximately 40–46 minutes per flight for the platform used) constrained continuous recording to discrete peak-period windows rather than a full-day, uninterrupted survey, although the second-day continuous recording partially addressed this limitation for volume-profile characterization. Second, detection accuracy may be sensitive to adverse weather (heavy rain, low light) and airspace regulations, which restricted flight altitude and, in turn, the achievable ground sampling distance; these constraints have been similarly noted as key operational challenges in the broader UAV traffic-monitoring literature (Gohari et al., 2022; Zandieh et al., 2023). Third, the capacity-analysis results are specific to the studied intersection's geometry, signal plan, and traffic composition and should not be generalized without site-specific validation elsewhere. Future research could extend this framework by integrating real-time UAV-to-signal-controller communication for adaptive signal control, following recent conceptual work on drone-assisted adaptive traffic management (Frontiers, 2025), and by expanding the training dataset to further improve detection accuracy for small and occluded vehicle classes.

CONCLUSIONS

This study developed and validated a UAV and computer vision-based framework for measuring traffic density and evaluating the level of service of a four-arm signalized intersection in Padang City, Indonesia. The fine-tuned YOLOv8 detector achieved an overall mAP@0.5 of 0.918, and the complete detection-and-tracking pipeline produced vehicle counts within 3.9% mean absolute percentage error of manual ground-truth counts, confirming that aerial computer-vision methods can provide accurate, efficient, and safer alternatives to conventional manual traffic surveys. Application of the resulting traffic volumes within the PKJI 2023 capacity-analysis framework revealed that the East and South approaches of the study intersection operate at or beyond capacity (degree of saturation up to 1.12) during peak periods, corresponding to LOS E–F conditions and average delays exceeding 60 s/pcu, while the North and West approaches maintained comparatively better performance (LOS C–D). These findings indicate an urgent need for signal-timing re-optimization, and potentially geometric improvement, at the East and South approaches. Beyond the specific case study, the results demonstrate the broader feasibility of integrating UAV aerial sensing with deep learning-based computer vision as a scalable, repeatable data-collection method to support intersection performance monitoring and evidence-based traffic management in Indonesian urban contexts.

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