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Development of a YOLOv8-Based Real-Time Vehicle Speed Estimation System for the Universitas Riau Campus

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Abstract: *This study introduces a low-cost, real-time vehicle speed estimation system for monitoring speed violations on the Universitas Riau campus, utilizing YOLOv8 object detection and smartphone-based video streaming. The system incorporates wireless video acquisition, centroid-based object tracking, and two-line virtual speed estimation, eliminating the need for radar, LiDAR, or camera calibration equipment. Experimental validation was performed on five campus road segments at controlled speeds of 30 km/h and 40 km/h, with additional tests at 50 km/h. The evaluation included motorcycles and passenger cars under various time periods and light rain conditions. Results show that the system achieved Mean Absolute Error (MAE) values between 0.98 and 1.22 km/h and Root Mean Square Error (RMSE) values between 0.99 and 1.10 km/h. The system reliably detected vehicle speed violations during controlled tests, supporting the feasibility of smartphone-based real-time traffic monitoring in campus settings.*

Keywords: *YOLOv8, Vehicle Speed Estimation, Real-Time Object Detection.*

1. Introduction

Traffic safety in educational zones presents a significant challenge for university administrations, especially in densely populated areas where pedestrians and various vehicle types interact. At Universitas Riau, this issue is primarily attributed to a large internal population, which by 2025 includes 38,120 active students, 1,383 permanent lecturers, and 902 educational staff [1]. The majority of this community depends on motorcycles and passenger cars for daily transportation, resulting in frequent conflict zones along campus roadways. Field observations and interviews with campus security personnel indicate that speed violations are common, particularly on roads without consistent manual supervision. This study is based on the Ministry of Transportation Regulation No. 111 of 2015, which stipulates a maximum speed limit of 30 km/h for campus and school zones to protect vulnerable road users [2]. Compliance with this regulation is essential, as excessive speed substantially increases collision forces and diminishes driver reaction times in areas with high pedestrian activity [3].

Conventional traffic enforcement methods at Universitas Riau, including manual patrols and radar guns, have been insufficient due to high operational costs, reliance on human operators, and technical limitations such as cosine errors and radio interference [4]. Previous local initiatives, such as the study by Muhammad Indra Setiabudi et al., "Implementation of the Frame Difference Method for Detecting Motorized Vehicle Speed at Universitas Riau," utilized a Raspberry Pi 3 Model B and a frame difference algorithm. Their system achieved an accuracy of 86.67% and introduced an automated PDF violation report system[2]. Despite these advancements, traditional frame-subtraction techniques are still vulnerable to ghosting effects, overlapping objects, and variable lighting conditions characteristic of the Riau climate [5].

To address these technical challenges and comply with the regulatory requirements of Ministry of Transportation Regulation No. 111 of 2015, this study introduces a robust real-time monitoring framework utilizing the YOLOv8 architecture. In comparison to previous deep learning models, YOLOv8 utilizes an advanced feature extraction architecture that enhances multi-scale object detection. This improvement enables reliable identification of motorcycles and passenger vehicles frequently present in campus traffic environments and ensures robust performance across diverse weather and lighting conditions [7]. Recent applications in university environments have demonstrated that YOLO-based systems provide greater detection stability and faster processing than traditional pixel-difference methods [8][9].

This study offers several key contributions: the development of a smartphone-based wireless acquisition system for flexible deployment, the integration of YOLOv8 with centroid-based tracking, and the implementation of two-line virtual speed estimation that does not require additional camera calibration [10]. The system is specifically designed for deployment along the main road segments of the Universitas Riau campus, such as Jl. Binawidya, Jl. Mochtar Luthfi, and high-traffic areas near the Faculty of Economics and Business, LPPM, and Faperika. By employing a low-cost smartphone-based approach and a calibration-free method, the proposed solution enables campus security to enforce safety regulations and automatically generate real-time evidence of speed violations [11].

2. Methods

A real-time vehicle speed estimation system was developed utilizing YOLOv8 for object detection and centroid-based tracking to monitor speed violations on the Universitas Riau campus. This system incorporates a cost-effective architecture that uses a smartphone camera for wireless video acquisition, and a GPU-based laptop as the primary processing unit [12]. The hardware configuration included a smartphone camera configured to capture video at 640 × 480 pixels and 30 frames per second, which streamed via Wi-Fi to a Lenovo Legion 5i laptop featuring an Intel Core i7-12800H processor, an NVIDIA RTX 3060 GPU, and 16 GB of RAM. Video frames were processed using Python 3.8, OpenCV, and Ultralytics YOLOv8 [13].

The object detection stage employed the YOLOv8s model to balance detection accuracy and inference speed, thereby supporting robust real-time performance on the designated processing unit. In contrast to larger variants, the small architecture achieves adequate precision while reducing computational demands, which is essential for deployment on resource-constrained hardware [6]. The detection confidence threshold was established at 0.5, and the Intersection over Union threshold for non-maximum suppression was set at 0.45. During inference, only two object classes were considered: motorcycle and car [7].

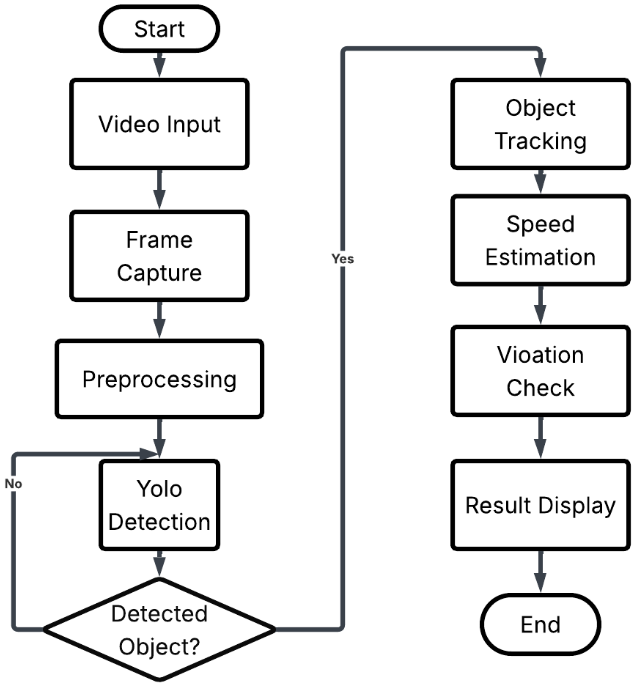

Figure 1. Flowchart of the Software

The system workflow, as depicted in the flowchart, consists of a sequential process that initiates with real-time video acquisition via a smartphone. Subsequent steps include frame resizing and normalization, YOLOv8-based vehicle detection, and centroid tracking using Euclidean distance to maintain object identities across frames [12]. This tracking approach enables vehicle speed estimation through a two-line virtual measurement technique [13].

Figure 2. A two-line virtual measurement approach

Vehicle speed estimation utilizes a two-line virtual measurement method, as illustrated in Figure 2. Two parallel virtual lines are manually defined within the camera's field of view. When the centroid of a tracked vehicle crosses the first line, the system records the initial timestamp t1. Upon crossing the second line, the system records timestamp t2. The travel time is then calculated as $\Delta t = t2 - t1$. The physical distance between the two lines is determined through manual pixel-to-meter calibration, in which 50 pixels correspond to a physical distance of 20 meters, as measured with a multiband GPS-based smartwatch [12][13]. Vehicle speed is calculated using the established distance-time relationship.

The experimental vehicles in this study included three passenger cars: Mitsubishi Xpander Cross, Toyota Corolla Altis, and Toyota Agya, as well as three motorcycles: Yamaha Grand Filano, Honda Vario 160, and Honda Revo. These vehicles were selected to represent variations in dimensions, body profiles, and motion characteristics commonly observed in campus traffic environments [6].

The smartphone camera was positioned at an observation angle of approximately 20° relative to the road direction. The distance between the camera and the initial virtual detection line was established at 30 meters. This measurement was conducted in the field using a smartwatch with multi-band GPS positioning to enhance spatial measurement consistency. Throughout all controlled experiments, traffic conditions remained light, with low vehicle density and minimal occlusion.

The testing procedure was conducted under controlled conditions at five road segments within the Universitas Riau campus: Mochtar Luthfi Road, FEB UNRI Road, LPPM Road, Binawidya Road, and Faperika Road. Two vehicle categories, motorcycles and passenger cars, were tested at controlled reference speeds of 30 km/h and 40 km/h across all locations. Additional 50 km/h testing was conducted at Mochtar Luthfi Road to evaluate system behavior at higher violation speeds. Each speed scenario involved 18 samples collected during morning, noon, and afternoon periods. Additional environmental validation was conducted during light rain conditions using 8 samples.

The ground-truth speed was measured using the test vehicle's digital speedometer during periods of stable acceleration. System performance was assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which were calculated by comparing estimated speeds to reference speedometer readings [6]. In accordance with traffic regulations set by Universitas Riau campus security management, the maximum allowable vehicle speed within the campus is 30 km/h [2]. Consequently, vehicles exceeding this limit were classified as speed violations during the system evaluation.

3. Results and Discussion

This section provides a performance evaluation of the proposed YOLOv8-based vehicle speed estimation system under controlled testing scenarios on the Universitas Riau campus. In contrast to the previous version, the current evaluation considers only metrics measured directly during experiments: average estimated speed, Mean Absolute Error, Root Mean Square Error, and violation-detection consistency. Metrics such as mean Average Precision (mAP) and object detection accuracy are excluded from this section, as they were not experimentally quantified in the present study. To enhance clarity and efficiency in data presentation, detailed per-vehicle measurements were consolidated into statistical results across five road locations, three time periods, and two environmental conditions. The ground-truth speed was determined using the vehicle's speedometer during controlled driving conditions.

Table 1. Summary of System Performance Under Normal Weather Conditions

Location	Test Speed (km/h)	Average Estimated Speed (km/h)	MAE (km/h)	RMSE (km/h)	Violation Detection
Mochtar Luthfi	30	28.97	1.03	1.01	No violation detected in all samples.
Mochtar Luthfi	40	38.93	1.07	1.04	All samples were identified as violations.
Mochtar Luthfi	50	48.88	1.12	1.06	All samples were identified as violations.
FEB UNRI	30	28.97	1.03	1.01	No violation detected in all samples.
FEB UNRI	40	39.01	0.99	1	All samples were identified as violations.
LPPM	30	28.99	1.01	1	No violation detected in all samples.
LPPM	40	38.94	1.06	1.03	All samples were identified as violations.
Binawidya	30	28.87	1.13	1.06	No violation detected in all samples.
Binawidya	40	38.78	1.22	1.1	All samples were identified as violations.
Faperika	30	29.02	0.98	0.99	No violation detected in all samples.
Faperika	40	38.9	1.1	1.05	All samples were identified as violations.

Table 1 shows that the system consistently produced estimated speeds slightly lower than the reference speedometer readings across all test locations. The average mean absolute error (MAE) ranged from 0.98 to 1.22 km/h, and the root mean square error (RMSE) ranged from 0.99 to 1.10 km/h. These findings suggest that the proposed method maintains stable estimation performance despite variations in road geometry, lighting conditions, and vehicle movement patterns. This level of performance is comparable to previous video-based approaches, such as those using YOLOv3 with DeepSORT and optical flow on fixed camera feeds, which reported MAE and RMSE values of 3.38 km/h and 4.69 km/h, respectively [13]. Projection-based methods employing perspective transformations at urban intersections achieved speed errors not exceeding 1.5 km/h after calibration [14]. Additionally, YOLOv8 variants in bidirectional lane scenarios yielded mean errors of ±0.98 m/s [7]. The present low-cost smartphone implementation demonstrates competitive accuracy without the need for specialized hardware or extensive calibration, consistent with findings from multi-vehicle YOLOv7-DeepSORT systems in resource-constrained developing regions, which maintained error rates below 3% through careful line positioning [12].

A consistent trend of underestimation was observed in nearly all experiments. Multiple technical factors contribute to this phenomenon. First, the pixel-to-meter conversion constant was determined manually, without automatic camera calibration, which can introduce scaling errors when the vehicle trajectory shifts relative to the camera viewpoint. Second, fluctuations in YOLO bounding-box coordinates across frames may compromise the stability of centroid tracking and directly affect travel-time measurements between virtual lines. Third, video streaming from the smartphone camera over Wi-Fi can introduce frame delays or temporal jitter, especially when network latency increases. These challenges are consistent with findings from previous studies, where manual distance measurements and line positioning using image tools introduced uncertainties that affected the final MAE/RMSE [12]. Unlike high-end fixed installations that achieve errors below 1.5 km/h using full geometric calibration [14], this approach focuses on being easy to deploy in campus settings.

While the system accurately identified all test samples based on the defined speed threshold in controlled experiments, these findings are applicable only to the current testing scenario. The sample size is limited, and the experiments were performed under controlled traffic conditions with minimal object occlusion. Previous studies employing YOLOv8 on highway datasets with 1920×1080 resolution also reported robust violation detection but highlighted the necessity for more extensive environmental testing [6][9].

Table 2. Performance Under Light Rain Conditions

Condition	Test Speed (km/h)	MAE (km/h)	RMSE (km/h)
Light Rain	30–40	1.08	1.04

Table 2 indicates that the system remained operational under light rain, exhibiting only a minor increase in estimation error relative to normal weather. These results indicate that the proposed system possesses robustness to moderate environmental variations, aligning with findings that YOLO-based detectors maintain performance in rainy or low-light scenarios through deep feature extraction [6][13]. Nevertheless, further experiments under heavier rain, nighttime conditions, denser traffic, and varying camera angles are required prior to broader deployment, as emphasized in comprehensive surveys of traffic anomaly detection methods [15].

Speed Violation Report

Generated on: 2026-03-03 17:36:50

Speed Limit: 30 km/h

Violation #1

Timestamp:	2026-03-03 17:36:50
Vehicle Type:	car
Recorded Speed:	38.8 km/h
Speed Limit:	30 km/h
Over Speed By:	16.8 km/h

Figure 3. Speed Violation Detection Results under Light Rain Conditions

The results demonstrate that the proposed smartphone-based YOLOv8 system accurately estimates vehicle speed in real time and detects speed violations with minimal error under campus traffic conditions. Figure 3 further substantiates system performance by presenting speed violation detection outcomes under light-rain conditions, accompanied by corresponding violation reports for each vehicle exceeding the speed limit. This study presents a cost-effective, real-time traffic monitoring system that integrates smartphone streaming, YOLOv8 object detection, centroid-based tracking, and two-line virtual speed estimation, eliminating the need for camera calibration. This methodology broadens the applicability of previous fixed-infrastructure solutions. Additionally, the system produces violation reports containing vehicle identification, timestamp, estimated speed, and violation status for vehicles exceeding the predefined speed threshold.

4. Conclusions

A real-time vehicle speed estimation system based on YOLOv8 was developed and evaluated for campus traffic monitoring, employing smartphone video streaming and centroid-based object tracking. Experimental evaluation across five road segments at Universitas Riau showed that the system achieved mean absolute error (MAE) values ranging from 0.98 to 1.22 km/h and root mean square error (RMSE) values ranging from 0.99 to 1.10 km/h in controlled scenarios involving motorcycles and passenger cars.

The results suggest that the proposed low-cost architecture provides reliable speed estimation and violation identification in controlled campus traffic conditions without the need for camera calibration. This study details the implementation of a flexible, smartphone-based traffic monitoring system that integrates YOLOv8 detection with two-line virtual speed estimation, specifically tailored for educational environments.

The present experiments were conducted under conditions of limited traffic density, controlled vehicle speeds, and relatively stable environmental factors. Therefore, the findings cannot be generalized to all traffic scenarios. Future research will involve testing under nighttime conditions, heavy rainfall, increased traffic density, varied camera viewing angles, and comparisons with advanced tracking algorithms such as SORT, DeepSORT, and ByteTrack.

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