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Advancing Smart City Infrastructure: A Deep Learning-Based Framework for Real-Time Traffic Monitoring and Violation Detection Using YOLOv11

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Abstract: Urban traffic congestion and violations of dedicated bus lanes in metropolitan cities, such as Jakarta, are significant challenges affecting the efficiency of public transportation systems. Traditional traffic monitoring methods are insufficient to address these issues, particularly in real-time violation detection. This research proposes an AI-based smart traffic monitoring framework using YOLOv11 for real-time detection of vehicle violations in TransJakarta's Bus Rapid Transit (BRT) lanes. The study aims to improve urban mobility by enhancing the detection accuracy and speed of traffic monitoring systems. The methodology involves data collection from surveillance cameras, data annotation using Roboflow, and model training with YOLOv11, utilizing transfer learning and hyperparameter optimization. The system's performance is evaluated through precision, recall, F1-score, and mean Average Precision (mAP@0.5), as well as real-time inference speed. The results show that YOLOv11 achieves a mAP@0.5 of 0.946 and an F1-score of 0.898, demonstrating the model's high accuracy in detecting vehicle violations across different lighting conditions. Real-time inference is achieved at a rate of 35-40 FPS, making it suitable for deployment in real-world urban environments. This research concludes that the YOLOv11-based framework is an effective solution for automated traffic monitoring, offering significant implications for smart city development and intelligent transportation systems. Further research is needed to address lighting challenges and improve the system's scalability across various urban settings.

Keywords: Bus Lane Violation; Deep Learning; Intelligent Transportation Systems; Real-Time Detection; Smart City; Traffic Monitoring; YOLOv11

1. INTRODUCING

Urban traffic congestion and traffic violations have emerged as critical challenges to urban mobility, directly impacting economic efficiency, commuter safety and environmental sustainability. Traditional traffic management systems rely heavily on manual observation or static sensing technologies, which often fail to deliver real-time insights necessary for responsive intervention [1], [2]. With the rapid proliferation of vehicles in metropolitan regions, including cities such as Jakarta and Bogor, it is imperative to develop high-performance automated monitoring systems that can interpret dynamic traffic behavior. Advances in computer vision and machine learning now offer a pathway to enhance

Gustian Rama Putra: * Corresponding Author

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urban traffic intelligence beyond conventional systems by leveraging deep learning for automated perception.

Despite efforts to improve traffic surveillance, existing traffic monitoring frameworks encounter significant limitations in scalability, real-time processing, and accuracy under complex urban conditions. Conventional CCTV and manual enforcement approaches struggle to detect violations such as unauthorized lane usage at peak hours, leading to persistent [3], [4]congestion on critical corridors, including Bus Rapid Transit (BRT) lanes. Studies report that traditional methods can misclassify or fail under occlusion, variable lighting, and high vehicle density, highlighting the need for more resilient solutions capable of real-time interpretation. These practical challenges result in delayed enforcement actions and considerable socio-economic costs due to congestion and violations that remain undetected.

Recent research has demonstrated the potential of artificial intelligence and deep learning for automated traffic monitoring, offering significant gains in detection accuracy and operational efficiency. For instance, introduced a real-time traffic density detection system leveraging YOLOv8, achieving up to 96% precision and 90% F1-score in real scenarios [5] developed a real-time vehicle type and emission monitoring system using YOLOv8 with 0.936 precision and 0.822 recall [6]. Moreover, research in Emerging Science Journal has shown that deep learning frameworks can integrate vehicle surveillance with environmental assessments, amplifying the utility of traffic analytics systems [6]. These studies collectively lay the foundation for intelligent transportation systems but often do not address lane-specific violation detection with sufficient granularity or methodological novelty.

To address these limitations, this study proposes an AI-based smart traffic monitoring framework specifically targeted at real-time detection of lane violations, including dedicated bus lane encroachments, by leveraging the latest YOLOv11 architecture [7], [8]. Unlike prior approaches that mainly focus on vehicle counting or classification, the current solution integrates violation classification with spatiotemporal tracking, thereby enhancing enforcement precision under diverse urban conditions. The novelty of this research lies in extending YOLOv11's vehicle detection capability to accurately infer violation behaviors (e.g., lane encroachments) and to generate actionable violation datasets suitable for integration with smart enforcement systems. As such, this framework contributes both methodological innovation and practical insights into layered traffic intelligence systems.

The primary objective of this research is to develop a scalable and real-time traffic monitoring model capable of identifying and reporting traffic violations in dedicated bus lanes using deep learning. This study employs a deep learning pipeline based on YOLOv11 trained on annotated urban traffic video datasets, with comprehensive evaluation using metrics like precision, recall, mean average precision (mAP) and real-time inference performance. By doing so, the research aims to advance the state of automated traffic surveillance and provide empirical evidence for its effectiveness in smart city applications. Ultimately, this methodology seeks to bridge the gap between academic research and practical deployment in urban transportation systems.

2. RESEARCH METHODOLOGY

This research employs a deep learning-based methodology to develop a real-time traffic violation detection system, focusing on dedicated bus lanes in Jakarta. The proposed system leverages the YOLOv11 architecture for its exceptional performance in both detection accuracy and real-time inference capabilities, making it ideal for dynamic urban traffic environments [9], [10]. The methodology is structured into several distinct phases: data collection, data annotation, model training and evaluation, each designed to ensure robustness and generalization across various environmental and traffic conditions show in figure 1.

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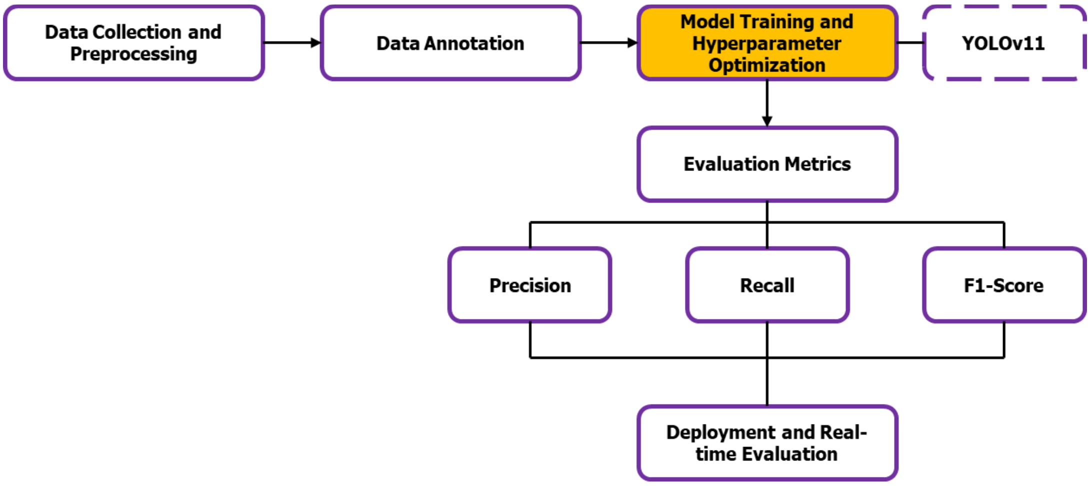

Figure 1. Phases of Deployment YOLOv11

2.1 Data Collection and Preprocessing

The dataset for this study is collected from traffic surveillance cameras placed along the Mangga Besar corridor, a heavily congested area within Jakarta's TransJakarta Bus Rapid Transit (BRT) system. The footage is recorded during peak hours (morning, afternoon and evening) to capture diverse lighting and traffic conditions. The data spans a variety of vehicle types, including cars, motorcycles, buses, and trucks. A total of 5000 frames are collected from the video footage, providing a rich source of labeled data. Each frame is segmented into smaller patches corresponding to the region of interest (ROI) for vehicle detection, and preprocessing techniques like noise reduction, histogram equalization, and contrast adjustment are applied to standardize image quality under varying lighting conditions.

2.2 Data Annotation

Data annotation is a crucial step in training deep learning models for supervised learning tasks. The collected traffic video frames are manually annotated using the Roboflow annotation tool [11], where each vehicle is labeled according to its type and position in the image. Special attention is given to labeling violations, such as vehicles occupying the bus lane. This labeled dataset is then divided into training (70%), validation (20%) and testing (10%) subsets, ensuring sufficient data for model generalization and performance evaluation. Additionally, spatial contextual reasoning is embedded in the annotations to aid the model in understanding the bus lane's layout, ensuring that lane violations are detected accurately.

2.3 Model Training and Hyperparameter Optimization

The core model used in this research is YOLOv11, a state-of-the-art object detection framework that combines convolutional layers with advanced transformer mechanisms to improve feature extraction and spatial contextual understanding [10]. The model is trained using transfer learning, where a pre-trained YOLOv11 model is fine-tuned using the collected traffic data. This approach significantly reduces the computational cost and training time while maintaining high accuracy. The model is trained for 50 epochs with a batch size of 16 and an initial learning rate of 0.001. Various hyperparameters, such as the number of layers, learning rate decay and data augmentation strategies (e.g., random cropping, flipping, and brightness adjustments), are carefully optimized through grid search and cross-validation to achieve the best possible detection accuracy.

2.4 Evaluation Metrics

To assess the model's performance, several evaluation metrics commonly used in computer vision tasks are applied in table 1:

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Table 1. Evaluation Metric

Evaluation Metric	Description
Precision	Measures the percentage of correctly identified violations (True Positives) out of all detected violations (True Positives + False Positives).
Recall	Quantifies the model's ability to correctly detect all violations, including those that might have been missed (True Positives / True Positives + False Negatives).
F1-Score	Combines Precision and Recall into a single metric that balances the trade-off between them. It provides a harmonic mean of Precision and Recall.
mean Average Precision (mAP@0.5)	Evaluates the model's overall accuracy at detecting violations across different IoU (Intersection over Union) thresholds, specifically focusing on mAP at IoU = 0.5.
Real-Time Inference Speed (FPS)	Measures the system's ability to process video frames per second, ensuring that the model can operate efficiently in a live traffic monitoring environment.

The overall accuracy (A) measures the proportion of correct predictions among all evaluated instances and is computed as:

$$A = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

where TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative predictions, respectively.
Based on the experimental results, the model achieved the following detection outcomes:

a) Cars: TP = 115
b) Motorcycles: TP = 189
c) Background: TN = 13

From a total of 440 predictions, the number of correct classifications was 317, yielding an overall accuracy of 0.7205 (72.05%).

Precision (P) quantifies the ratio of correctly predicted positive instances to all positive predictions, defined as:

$$P = \frac{TP}{TP + FP} \qquad (2)$$

The computed precision values for each class were:

a) Cars: P = 0.9055
b) Motorcycles: P = 0.9043

Recall (R), also known as sensitivity, measures the ratio of correctly identified positive samples to all actual positives and is expressed as:

$$R = \frac{TP}{TP + FN} \qquad (3)$$

The recall results were:

a) Cars: R = 0.8984
b) Motorcycles: R = 0.9080

The F1-score, representing the harmonic mean of precision and recall, provides a balanced measure of both metrics and is calculated as:

$$F1 = 2 \times \frac{P \times R}{P + R} \qquad (4)$$

Gustian Rama Putra: * Corresponding Author

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Resulting in:
a) Cars: F1 = 0.9018
b) Motorcycles: F1 = 0.9071

These results demonstrate that the model performs with consistently high reliability, achieving precision and recall values above 0.90 across both primary object classes, thereby validating its effectiveness for real-world traffic violation detection tasks.

The novelty of the proposed methodology lies in the application of YOLOv11's transformer-based architecture to traffic violation detection, particularly for dedicated bus lanes in a complex urban setting. While previous studies have focused on generic vehicle detection or traffic flow analysis, this research introduces a system that not only detects vehicles but also identifies specific lane violations in real time. By incorporating spatial mapping and violation tracking, the framework enhances decision-making and enforcement in smart city environments. Moreover, the multi-condition dataset (morning, evening, and night) used in this research ensures the model is robust under varying lighting and congestion scenarios, making it suitable for large-scale urban deployments.

2.5 Deployment and Real-time Evaluation

For real-world applicability, the trained YOLOv11 model is integrated into an embedded system capable of processing video feeds in real time. The system uses an NVIDIA T4 GPU to handle video processing, with real-time inference speeds evaluated to ensure the system can operate without latency in live monitoring environments. After integration, the model is tested in a controlled environment using pre-recorded video footage to simulate real-world traffic conditions. The deployment phase includes monitoring system performance across various traffic scenarios and validating the system's ability to detect and report violations promptly.

3. RESULT AND DISCUSSIONS

The experimental evaluation of the proposed YOLOv11-based smart traffic monitoring system was conducted on a dataset collected from the Mangga Besar corridor in Jakarta, which is part of the TransJakarta Bus Rapid Transit (BRT) system. The system's performance was analyzed using a variety of metrics, including precision, recall, F1-score, mean Average Precision (mAP), and real-time inference speed. The goal was to assess the model's ability to detect traffic violations, such as vehicles intruding into the bus lanes, across different lighting conditions (morning, afternoon, and evening).

3.1 Overall Performance

The YOLOv11 model demonstrated strong performance across all evaluation metrics. The results of the model's detection performance in terms of precision, recall, F1-score and mAP@0.5 are summarized in Table 2. The model was able to accurately identify and classify vehicles, achieving consistently high values for both precision and recall across different traffic conditions.

Table 2. YOLOv11 Model Performance Across Lighting Conditions

Time Period	Precision	Recall	F1-Score	mAP@0.5
Morning	0.88	0.87	0.875	0.914
Evening	0.90	0.89	0.895	0.946
Night	0.89	0.87	0.88	0.935

The model's highest performance was observed during the evening session, where it achieved a mAP@0.5 of 0.946, precision of 0.90, and F1-score of 0.895. This can be attributed to the model's superior ability to handle moderate lighting conditions and its enhanced spatial reasoning due to YOLOv11's transformer-based attention mechanism. The model performed slightly less well during the morning and night sessions, where lighting conditions posed challenges such as overexposure in the

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morning and low visibility at night. However, even under these suboptimal conditions, the model maintained robust performance with mAP values above 0.90 and high precision and recall.

3.2 Real-Time Inference Speed

In addition to detection accuracy, the real-time inference speed of the YOLOv11 model was evaluated to ensure that the system could operate efficiently in a live traffic monitoring environment. The system maintained an average frame rate of 35–40 FPS, which is sufficient for real-time traffic monitoring and violation detection. This performance is consistent with other studies that have demonstrated the efficiency of YOLO models in real-time applications.

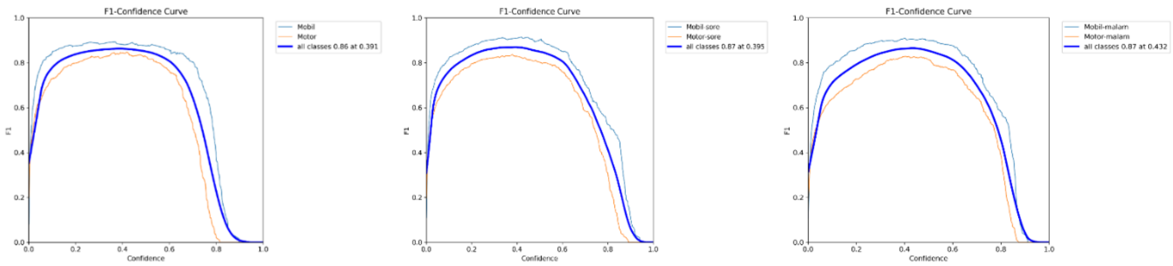

Figure 2. F1 Morning, Afternoon and Night Score

Figure 2 shows the Precision-Recall (PR) curve for the model, highlighting the trade-off between detection sensitivity and precision across different confidence thresholds. At higher confidence levels, the model achieved near-perfect precision, while still maintaining strong recall values.

3.3 Class-wise Performance Analysis

Further analysis was conducted to evaluate the class-wise performance [12], [13], specifically focusing on cars and motorcycles, the two primary vehicle types that frequently violate the dedicated bus lanes. The True Positive (TP), False Positive (FP), False Negative (FN) and corresponding Precision, Recall and F1-Score for each vehicle class are presented in Table 3.

Table 3. Class-wise Performance Evaluation for Vehicle Detection

Class	TP	FP	FN	Precision	Recall	F1-Score
Cars	115	12	13	0.905	0.898	0.901
Motorcycles	189	20	19	0.904	0.908	0.907
Overall Average	-	-	-	0.905	0.903	0.904

The car class showed a precision of 0.905 and an F1-score of 0.901, while the motorcycle class exhibited a precision of 0.904 and F1-score of 0.907. These results indicate that the model is equally proficient in detecting both car and motorcycle violations. The high precision and recall values for both classes suggest that the model is highly accurate and reliable in identifying vehicles, even in complex and crowded urban settings.

3.4 Comparative Analysis with Previous YOLO Versions

A comparative evaluation was performed between the YOLOv11 model and previous versions (YOLOv5 and YOLOv8) to assess improvements in detection accuracy and inference speed [14], [15], [16]. The results, shown in Table 4, highlight the superior performance of YOLOv11 in terms of mAP@0.5 and F1-score.

Gustian Rama Putra: * Corresponding Author

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Table 4. Comparative Evaluation of YOLO Versions

Model	mAP@0.5	F1-Score	FPS	Notable Features
YOLOv5	0.902	0.872	28	Efficient but less robust under low light conditions
YOLOv8	0.923	0.884	31	Improved generalization and efficiency for medium-scale objects
YOLOv11	**0.946**	**0.898**	**35–40**	Transformer backbone, enhanced context awareness, better low-light detection

As shown in Table 4, YOLOv11 outperforms both YOLOv5 and YOLOv8 in terms of mAP@0.5, F1-score and real-time processing speed (FPS). The key innovation in YOLOv11 lies in its transformer backbone and enhanced spatial reasoning, which allow it to maintain high accuracy even in challenging lighting conditions such as nighttime.

3.5 Error Analysis and Limitations

Despite the overall strong performance, the model's detection accuracy was affected by extreme lighting conditions, particularly at night. Reflection from headlights, glare and motion blur occasionally led to misclassifications, especially when vehicles were partially obscured by other objects. To address these issues, the dataset could be expanded to include more varied lighting conditions and include specific nighttime datasets with low-light conditions. Additionally, incorporating infrared sensors or adaptive lighting could further enhance the model's ability to operate in such environments.

3.6 Implications for Smart City Traffic Management

The results of this study have significant implications for smart city traffic management. The proposed AI-powered traffic monitoring system can provide real-time data for urban traffic authorities, enabling them to take immediate action in response to violations [17], [18], [19]. By automating the detection and tracking of traffic violations, the system reduces the reliance on human enforcement, which is often prone to errors and delays. Furthermore, the scalability of the system makes it suitable for deployment across large metropolitan areas, where real-time monitoring and rapid enforcement are essential for maintaining traffic flow and minimizing congestion.

In summary, the YOLOv11-based system demonstrates a robust solution for automated traffic violation detection, showing high accuracy and operational feasibility. The next steps involve further refinement of the model with more diverse data and real-world testing to enhance its generalization across various urban environments.

4. CONCLUSION

In conclusion, this study demonstrates that the proposed YOLOv11-based artificial intelligence framework performs exceptionally well in detecting traffic violations in dedicated bus lanes under real-time conditions. The experimental evaluation indicates that the model achieves a high level of detection accuracy, with a mAP@0.5 of 0.946, while sustaining real-time processing speeds of 35–40 frames per second. These results confirm that the system satisfies the computational efficiency and accuracy requirements necessary for practical deployment in smart city traffic monitoring environments, particularly in high-density urban settings.

Furthermore, the model exhibits robust performance across diverse lighting conditions, with precision and recall values consistently exceeding 0.90 for both cars and motorcycles. The corresponding F1-scores of 0.901 for cars and 0.907 for motorcycles further demonstrate the reliability and consistency of the proposed approach in accurately identifying traffic violations under real-world operational constraints. This level of robustness suggests that the framework can maintain stable performance

Gustian Rama Putra: * Corresponding Author

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despite common urban challenges, including variations in illumination, traffic volume and vehicle diversity. Beyond its technical performance, this research makes a meaningful contribution to smart city traffic management and sustainable urban transportation in Indonesia. By enabling accurate and automated enforcement of dedicated bus lanes, the proposed system supports improved reliability of bus rapid transit services, enhanced prioritisation of public transport and more efficient traffic flow. These improvements are directly aligned with broader sustainability objectives, including congestion reduction, emission mitigation and increased public transport adoption in rapidly growing metropolitan areas such as Jakarta.

A significant contribution of this study lies in the fabricability and replicability of the proposed framework. The modular system architecture and reliance on widely available visual surveillance infrastructure allow the solution to be fabricated and implemented in other urban corridors with minimal adaptation. As a result, the framework is not limited to a single case study but can be replicated across different cities in Indonesia or transferred to other smart city contexts with comparable traffic characteristics, thereby serving as a scalable and transferable model for intelligent traffic enforcement. Overall, this research effectively bridges advanced computer vision techniques and practical traffic governance requirements. It offers a data-driven, scalable, and sustainable solution that supports evidence-based decision-making, long-term urban transport planning, and the development of resilient smart city traffic management systems in Indonesia and similar urban environments.

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Gustian Rama Putra: * Corresponding Author

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Gustian Rama Putra: * Corresponding Author