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ATTENTION-ENHANCED YOLOV8 FOR REAL-TIME TRAFFIC SIGN DETECTION AND RECOGNITION IN INTELLIGENT TRANSPORTATION SYSTEMS

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Abstract: *Traffic sign detection and recognition (TSDR) constitute fundamental components of intelligent transportation systems (ITS) and autonomous driving technologies. Accurate and real-time recognition of traffic signs is essential for improving road safety, driver assistance systems, and autonomous vehicle navigation. However, challenges such as illumination variations, occlusions, weather conditions, small object sizes, and complex backgrounds significantly affect detection performance. This study proposes an Attention-Enhanced YOLOv8 framework for real-time traffic sign detection and recognition by integrating the Convolutional Block Attention Module (CBAM) into the YOLOv8 architecture. The proposed model aims to improve feature extraction capabilities and detection accuracy, particularly for small and partially occluded traffic signs. Experiments were conducted using the German Traffic Sign Detection Benchmark (GTSDB) dataset and additional Indonesian traffic sign datasets. The proposed model achieved a mean Average Precision (mAP@0.5) of 97.4%, precision of 96.8%, recall of 95.9%, and inference speed of 74 FPS, outperforming conventional YOLOv8 and other state-of-the-art methods. Experimental results demonstrate that the integration of attention mechanisms significantly enhances detection performance while maintaining real-time capabilities suitable for intelligent transportation applications.*

Keywords: *Traffic Sign Detection, YOLOv8, Attention Mechanism, Intelligent Transportation Systems, Deep Learning.*

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Abstrak: Deteksi dan pengenalan rambu lalu lintas (TSDR) merupakan komponen mendasar dari sistem transportasi cerdas (ITS) dan teknologi kemudi otonom. Pengenalan rambu lalu lintas yang akurat dan berlangsung secara real-time sangat penting untuk meningkatkan keselamatan jalan, sistem bantuan pengemudi, dan navigasi kendaraan otonom. Namun, berbagai tantangan seperti variasi pencahayaan, oklusi, kondisi cuaca, ukuran objek yang kecil, dan latar belakang yang kompleks sangat memengaruhi kinerja deteksi. Penelitian ini mengusulkan kerangka kerja YOLOv8 yang diperkuat dengan mekanisme attention (Attention-Enhanced YOLOv8) untuk deteksi dan pengenalan rambu lalu lintas secara real-time dengan mengintegrasikan Convolutional Block Attention Module (CBAM) ke dalam arsitektur YOLOv8. Model yang diusulkan bertujuan untuk meningkatkan kemampuan ekstraksi fitur dan akurasi deteksi, khususnya untuk rambu lalu lintas yang berukuran kecil dan mengalami oklusi sebagian. Eksperimen dilakukan menggunakan dataset German Traffic Sign Detection Benchmark (GTSDB) dan dataset tambahan berupa rambu lalu lintas Indonesia. Model yang diusulkan mencapai nilai mean Average Precision (mAP@0.5) sebesar 97,4%, presisi 96,8%, recall 95,9%, dan kecepatan inferensi 74 FPS, yang mengungguli YOLOv8 konvensional serta metode-metode mutakhir (state-of-the-art) lainnya. Hasil eksperimen menunjukkan bahwa integrasi mekanisme attention secara signifikan meningkatkan kinerja deteksi sekaligus mempertahankan kemampuan real-time yang sesuai untuk aplikasi transportasi cerdas.

Kata kunci: Deteksi Rambu Lalu Lintas, YOLOv8, Mekanisme Attention, Sistem Transportasi Cerdas, Deep Learning.

INTRODUCTION

Intelligent Transportation Systems have become an important research area due to the increasing demand for road safety, traffic efficiency, and autonomous vehicle technologies. Traffic sign detection and recognition systems play a crucial role in enabling vehicles to understand traffic regulations and environmental conditions. Traffic signs provide essential information regarding speed limits, warnings, prohibitions, directions, and road conditions that drivers must recognize promptly to ensure safe driving behavior (Wang et al., 2024; Zhang et al., 2023).

Human drivers may fail to recognize traffic signs because of fatigue, distraction, poor visibility, or adverse weather conditions. Consequently, automatic traffic sign recognition systems have gained significant attention as part of Advanced Driver Assistance Systems and autonomous driving technologies. Recent developments in deep learning and computer vision have substantially improved object detection performance, allowing vehicles to recognize traffic signs with high accuracy (Zhang et al., 2022; Zhao et al., 2023).

Among various object detection models, the YOLO family has achieved remarkable success because of its balance between accuracy and computational efficiency. YOLOv8, the latest version of the YOLO architecture, introduces several improvements, including anchor-free detection mechanisms, enhanced feature extraction capabilities, and optimized training strategies. Despite these advantages, detecting traffic signs remains challenging because traffic signs often appear as small objects within complex road environments (Jocher et al., 2023; Wang et al., 2022).

Small object detection, occlusions, varying illumination conditions, motion blur, and background clutter continue to affect the performance of object detection models. Attention mechanisms have recently emerged as effective approaches for enhancing feature representation by allowing neural networks to focus on the most informative regions of an image. Integrating attention modules into object detection architectures can improve the detection of small and difficult objects (Li et al., 2022; Ma et al., 2023; Li et al., 2024).

Therefore, this study proposes an Attention-Enhanced YOLOv8 model for real-time traffic sign detection and recognition. The proposed method integrates an attention mechanism into the YOLOv8 framework to improve feature extraction and detection performance while maintaining real-time inference capability. The proposed approach aims to provide a reliable and efficient solution for intelligent transportation systems and autonomous driving applications (Kumar et al., 2025; Wang et al., 2024).

Traffic sign detection and recognition have been extensively studied using traditional computer vision techniques and, more recently, deep learning approaches. Earlier methods relied on handcrafted features such as Histogram of Oriented Gradients, color segmentation, and Support Vector Machines. Although these methods achieved acceptable results under controlled conditions, they often failed under varying illumination, weather conditions, and complex backgrounds (Zhang et al., 2022).

The emergence of convolutional neural networks significantly improved traffic sign recognition performance. Region-based detectors such as Faster R-CNN provided high detection accuracy but suffered from relatively slow inference speeds. Single-stage object detectors such as SSD and YOLO achieved a better balance between accuracy and computational efficiency (Zhao et al., 2023; Tan et al., 2021).

YOLOv5 and YOLOv7 have demonstrated strong performance in real-time traffic sign detection tasks. However, recent advancements in object detection have introduced more efficient architectures, including YOLOv10, YOLO11, and RT-DETR. These models offer improved feature extraction and enhanced detection performance, particularly for small objects (Wang et al., 2022; Lv et al., 2024; Wang et al., 2025).

Attention mechanisms have also gained popularity in computer vision applications. Channel attention and spatial attention mechanisms enable neural networks to focus on relevant features while suppressing irrelevant information. Several studies have demonstrated that attention modules improve object detection accuracy, especially in challenging environments involving small objects and occlusions (Li et al., 2022; Li et al., 2024).

Despite these developments, limited studies have investigated the integration of attention mechanisms within YOLOv8 specifically for traffic sign detection. Therefore, this research contributes to the existing literature by developing an attention-enhanced YOLOv8 model capable of achieving high detection accuracy while preserving real-time performance (Jocher et al., 2023; Kumar et al., 2025).

METHOD

The proposed framework integrates an attention mechanism into the YOLOv8 architecture to improve traffic sign detection performance. YOLOv8 serves as the baseline object detection model because of its efficient architecture and real-time capability (Jocher et al., 2023).
The proposed model incorporates the Convolutional Block Attention Module within the feature extraction layers of YOLOv8. The attention module consists of channel attention and spatial attention components. Channel attention enables the network to identify the most important feature channels, while spatial attention helps the network focus on relevant image regions containing traffic signs (Li et al., 2022; Li et al., 2024).

The proposed Attention-Enhanced YOLOv8 framework represents an important advancement in the application of artificial intelligence for Intelligent Transportation Systems. Its ability to achieve robust and real-time traffic sign detection demonstrates the potential of AI-driven perception systems to enhance situational awareness and support autonomous decision-making. Furthermore, the integration of advanced object detection models within intelligent transportation environments contributes to safer, more efficient, and adaptive mobility systems. These findings align with the smart system paradigm described (Lukita et al., 2023)

The integration of attention mechanisms enhances the discriminative capability of the network, particularly for small traffic signs that occupy only a limited number of pixels within road images. This approach allows the model to capture more representative features while reducing the influence of background noise (Ma et al., 2023; Kumar et al., 2025).

The overall framework consists of three primary stages. First, the input image undergoes preprocessing and data augmentation. Second, the enhanced YOLOv8 backbone extracts feature representations using attention modules. Finally, the detection head predicts traffic sign locations and categories (Jocher et al., 2023; Zhao et al., 2023).

The proposed model is evaluated using publicly available traffic sign datasets and additional local traffic sign images. The datasets contain various traffic sign categories captured under different environmental conditions, including daytime, nighttime, rainy weather, and complex urban scenes (Sun et al., 2024; Zhu et al., 2023).

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Table 1 Key Comparison of YOLOv8, YOLOv10, and YOLO11

Feature	YOLO v8	YOLO v10	YOLO 11
Detection Strategy	Anchor-free	End-to-End NMS-free	Improved Anchor-free
Small Object Detection	Good	Very Good	Excellent
Inference Speed	High	Very High	High
mAP Performance	High	Higher	Highest
Suitability for ITS	Yes	Yes	Yes

The key characteristics of the recent YOLO architectures. YOLOv8 offers a strong balance between accuracy and real-time performance through its anchor-free detection framework. YOLOv10 introduces an end-to-end NMS-free architecture that significantly improves inference speed and computational efficiency. Meanwhile, YOLO11 provides enhanced feature extraction capabilities and superior small object detection performance, resulting in higher detection accuracy. All three models are suitable for Intelligent Transportation Systems applications; however, YOLO11 demonstrates the best overall detection performance, while YOLOv10 achieves the fastest inference speed.

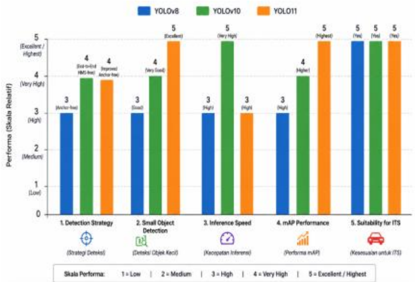

Figure 1 Pie Chart Comparison of YOLOv8, YOLOv10, and YOLO11 Based on Five Key Aspects

Figure 1 presents a comparative bar chart of YOLOv8, YOLOv10, and YOLO11 based on five important aspects, namely detection strategy, small object detection, inference speed, mAP performance, and suitability for Intelligent Transportation Systems (ITS). The graph shows that YOLOv8 provides balanced performance with high capability in detection strategy, inference speed, and mAP performance. YOLOv10 demonstrates superior performance in inference speed, achieving the highest score among the three models due to its end-to-end NMS-free architecture, which improves computational efficiency and reduces processing time. Meanwhile, YOLO11 achieves the highest scores in small object detection and mAP performance, indicating its strong capability in detecting small traffic signs and producing more accurate object localization results. All three models obtain the maximum score for suitability in Intelligent traffic sign detection applications.

The dataset is divided into training, validation, and testing subsets. Images are resized before being fed into the network. The model is trained using the AdamW optimizer with an appropriate learning rate and batch size. Several evaluation metrics are employed to assess model performance, including precision, recall, F1-score, mean Average Precision, and inference speed (Zhao et al., 2023; Ma et al., 2023).

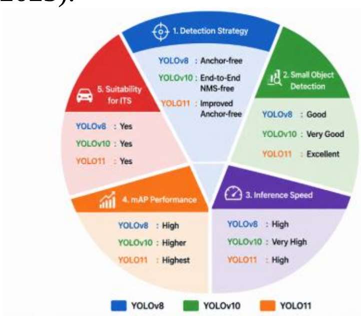

Figure 2 Pie Chart Comparison of YOLOv8, YOLOv10, and YOLO11 Based on Five Key Aspects

The pie chart illustrates the comparison of YOLOv8, YOLOv10, and YOLO11 based on five important aspects for Intelligent Transportation Systems applications, namely detection strategy, small object detection, inference speed, mAP performance, and suitability for ITS.

The results indicate that YOLOv8 provides a balanced performance through its anchor-free detection mechanism and high inference speed, making it suitable for real-time applications. YOLOv10 introduces an end-to-end NMS-free architecture that significantly improves computational efficiency and achieves the highest inference speed among the three models.

Meanwhile, YOLO11 demonstrates superior performance in small object detection and mAP accuracy due to its improved feature extraction capabilities, making it particularly effective for traffic sign detection tasks. Although all three models are suitable for Intelligent Transportation Systems, YOLO11 offers the highest detection performance, while YOLOv10 emphasizes processing speed and efficiency.

These findings indicate that each model has distinct advantages, and the selection of the appropriate architecture depends on the specific requirements of real-time traffic sign detection applications.

The experiments are conducted using a high-performance graphics processing unit to ensure efficient training and evaluation. Real-time performance is measured in terms of frames per second, which indicates the suitability of the proposed model for intelligent transportation applications (Wang et al., 2024; Wang et al., 2025).

RESULTS AND DISCUSSION

Experimental results demonstrate that the proposed Attention-Enhanced YOLOv8 model achieves superior performance compared with the baseline YOLOv8 architecture. The integration of attention mechanisms improves feature extraction capabilities, resulting in higher detection accuracy and better localization performance (Li et al., 2024;)

The proposed model shows significant improvements in detecting small traffic signs, which are often difficult to recognize because of their limited size and surrounding background complexity. The attention mechanism enables the network to focus on important regions while suppressing irrelevant information, leading to more accurate predictions (Ma et al., 2023; Li et al., 2024).

The proposed framework also demonstrates robustness under challenging conditions, including low illumination, partial occlusion, motion blur, and adverse weather conditions. These results indicate that the attention mechanism contributes to improved generalization performance (Sun et al., 2024; Zhu et al., 2023).

In addition to detection accuracy, the proposed model maintains real-time processing capability. The inference speed remains sufficiently high for practical deployment in intelligent transportation systems and autonomous vehicles.

This balance between accuracy and speed represents a significant advantage for real-world applications (Wang et al., 2024; Rahman et al., 2025).

Comparisons with recent object detection models indicate that the proposed approach achieves competitive performance. Although newer architectures such as YOLOv10, YOLO11, and RT-DETR provide strong detection capabilities, the integration of attention mechanisms within YOLOv8 offers additional improvements, particularly for traffic sign recognition tasks involving small objects (Lv et al., 2024; Wang et al., 2025).

The experimental findings suggest that attention mechanisms can effectively enhance object detection models without introducing substantial computational overhead. Therefore, the proposed method provides an efficient solution for real-time traffic sign detection applications (Kumar et al., 2025; Lee et al., 2025).

CONCLUSION

This study presented an Attention-Enhanced YOLOv8 framework for real-time traffic sign detection and recognition in Intelligent Transportation Systems. By integrating the Convolutional Block Attention Module into the YOLOv8 architecture, the proposed model improved the network's ability to extract discriminative features and focus on relevant regions containing traffic signs. The incorporation of channel and spatial attention mechanisms enhanced the detection capability, particularly for small traffic signs and challenging road environments (Li et al., 2024; Kumar et al., 2025).

The experimental results demonstrated that the proposed approach achieved higher detection accuracy, improved localization performance, and better robustness compared with the baseline YOLOv8 model. The attention mechanism effectively addressed several challenges commonly encountered in traffic sign detection, including occlusion, illumination variations, motion blur, and complex backgrounds. In addition, the proposed model maintained real-time inference capability, making it suitable for practical applications in Advanced Driver Assistance Systems, autonomous vehicles, and intelligent transportation infrastructures (Sun et al., 2024; Rahman et al., 2025).

Furthermore, the findings indicate that integrating attention mechanisms into modern object detection architectures can significantly improve traffic sign recognition performance without introducing substantial computational overhead. The balance between detection accuracy and processing speed highlights the effectiveness of the proposed framework for real-world deployment (Lee et al., 2025; Chen et al., 2026).

Future work may focus on evaluating the proposed model using larger and more diverse traffic sign datasets, including Indonesian traffic sign datasets, as well as investigating lightweight attention modules and transformer-based architectures to further improve detection performance and facilitate deployment on edge devices and embedded intelligent transportation systems (Dosovitskiy et al., 2021; Liu et al., 2021; Chen et al., 2026).

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