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Detection and Classification of Vehicle in Traffic Video using DL Algorithm

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Abstract: This work proposes a comprehensive approach utilizing the YOLOv8 deep learning algorithm to enhance vehicle detection and classification in intelligent transportation systems (ITS). The methodology involves meticulous dataset preparation, including diverse traffic videos and pre-processing techniques to ensure dataset quality. Leveraging the YOLOv8 algorithm implemented through the Ultralytics framework, the model is fine-tuned using transfer learning on custom datasets. Results demonstrate the effectiveness of the YOLOv8 model in accurately detecting and classifying vehicles, with further enhancements achieved through model optimization techniques like hyperparameter tuning and post-processing methods. The findings contribute to advancing computer vision and deep learning applications in transportation, paving the way for improved traffic management systems and autonomous vehicle technology.

Keywords: Vehicle Detection, Vehicle Identification, YOLOv8, Deep Learning, Intelligent Transportation Systems.

I. INTRODUCTION

Intelligent Transportation Systems (ITS) are crucial for modern urban planning, providing innovative solutions to tackle traffic congestion, enhance road safety, and optimize transportation efficiency. The accuracy of vehicle detection and classification remains a significant challenge in ensuring the effectiveness of ITS. In their comprehensive survey on vehicle detection methods, Maity et al.[1] thoroughly analyze existing approaches based on Faster R-CNN and YOLO architectures, providing insights into their architectures, interrelations, limitations, and future research directions Traditional methods, relying on manual surveillance and rule-based systems, face scalability and adaptability issues, necessitating more advanced approaches. In response, deep learning techniques, notably the You Only Look Once (YOLO) algorithm, have emerged as a game-changer in computer vision. Recent advancements in transportation detection systems, exemplified by the work of Shukhair et al., highlight the efficacy of employing the YOLOv5 algorithm for accurate and efficient detection of public transportation vehicles [2]. Li et al. [3] introduced an optimized YOLOv4-based model for object detection, along with a fine-tuned approach for pedestrian pose estimation.

Their system, incorporating Explainable AI technology, achieved a 74% reduction in parameters and a 2.6% improvement in detection precision. Qiu et al. developed a target detection algorithm, FE-CNN, based on deep learning technologies, improving recognition precision and convergence speed. Their approach shows real-time performance and accurate target detection in real traffic scenes [4]. YOLOv8, the latest iteration of this algorithm, offers real-time performance and superior accuracy in object detection tasks. The approach begins with the meticulous curation of a diverse dataset, comprising video footage from various surveillance sources, ensuring comprehensive coverage of traffic scenarios.

Implementation of YOLOv8 using the Ultralytics framework enables efficient model training and deployment. Leveraging transfer learning techniques, the model is fine-tuned to adapt to specific traffic conditions and vehicle classes, thereby enhancing its accuracy and robustness. By capitalizing on the capabilities of YOLOv8, this research aims to redefine the landscape of vehicle detection and classification, promising advancements in ITS solutions and the realization of autonomous driving technologies.

The outcomes of this work have profound implications for urban mobility, offering potential improvements in traffic management, safety measures, and operational efficiency in transportation systems. Through the integration of deep learning algorithms like YOLOv8, cities can proactively address traffic challenges, fostering safer, smarter, and more sustainable urban environments. Sindhu's project utilizes YOLOv4 for real-time vehicle identification from traffic video surveillance the framework includes pre-processing, image capture, and performance evaluation for potential real-time accident detection [5].

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II. METHODOLOGY

This proposed approach as shown in Fig. 1, details the approach utilized for accurate and efficient vehicle detection and classification using the YOLOv8 deep learning algorithm. The methodology encompasses dataset preparation, YOLOv8 implementation, training process, evaluation metrics, results analysis, and model optimization techniques. Each step is carefully designed to ensure robustness, scalability, and effectiveness in real-world traffic scenarios.

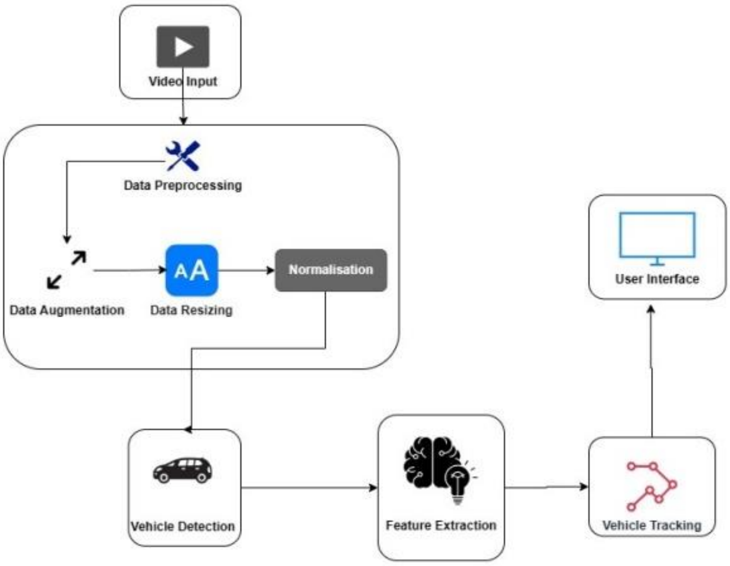

Fig. 1 Proposed Methodology

The proposed methodology utilizes machine learning for vehicle detection and feature extraction within a video data pipeline. Pre-processing steps, including noise reduction and normalization, prepare the data for an object detection module, likely employing a deep learning approach. Following vehicle detection, feature extraction captures relevant characteristics for further analysis. In line with recent advancements in vehicle detection and classification methodologies, our approach draws inspiration from the work of Zuraimi and Zaman [6], who utilized the YOLOv4 algorithm combined with DeepSORT for robust vehicle detection and tracking. Building upon their findings, we leverage the YOLOv8 deep learning algorithm in our proposed methodology to enhance the accuracy and efficiency of vehicle detection and classification.

A. Dataset Preparation

The dataset utilized in this study undergoes meticulous curation to encompass diverse scenarios encountered in real-world traffic environments, the details of train,validate and test data is shown in Table 1. It comprises extensive video footage collected from various traffic scenarios using mobile cameras, ensuring a comprehensive representation of traffic dynamics. Each frame in the dataset is meticulously annotated with bounding boxes around vehicles of interest, capturing a wide spectrum of vehicle types, sizes, and orientations.

TABLE I DETAILS OF DATASET

train	test	valid
2100	450	450

This dataset is used to train the YOLOv8 model in detecting and identifying classes of 5 vehicles namely, 'car', 'bus', 'truck', 'pickup', 'truck', van '.

To augment dataset diversity and enhance robustness, a series of pre-processing techniques are employed. Frame extraction is utilized to isolate individual frames from video sequences, facilitating detailed annotation and analysis. Furthermore, data augmentation techniques such as random rotation, flipping, and scaling are applied to diversify the dataset, thereby mitigating the risk of overfitting and enhancing model generalization capabilities.

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B. YOLOv8 Implementation

The implementation of the YOLOv8 algorithm is carried out leveraging the Ultralytics framework after meticulously curating the dataset, following the approach detailed by Shekade et al. [7], for efficient model training and deployment for object detection tasks. Ultralytics open-source library provides a robust platform for both training and deploying deep learning models, particularly suited for object detection tasks. Leveraging YOLOv8's architecture, characterized by its single-stage object detection approach and feature pyramid network, enables precise localization and classification of vehicles in diverse traffic scenarios. Nguyen et al. [8] proposed several improvements to the YOLOv5 architecture, focusing on redesigning the backbone and neck modules using lightweight convolutional network architectures like EfficientNet, PP-LCNet, and MobileNet to enhance the performance and speed of vehicle detection in traffic management and control systems. Transfer learning is a key aspect of the implementation process, allowing for the adaptation of the pre-trained YOLOv8 model to the custom dataset. By initializing the model with weights learned from a large-scale dataset, transfer learning expedites convergence and enhances performance on the target task. The YOLOv8 Architecture is depicted below in Fig. 2.

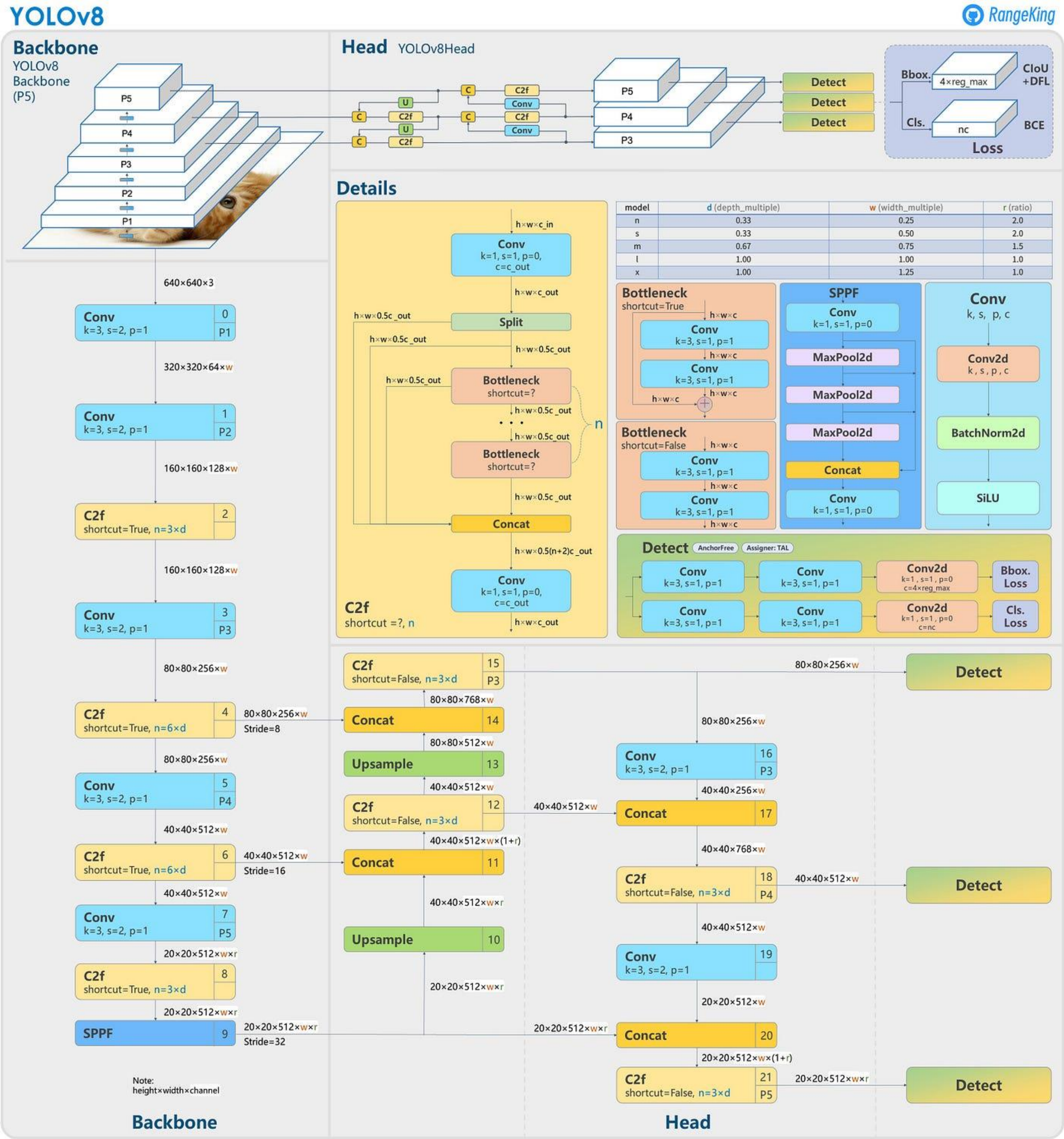

Fig. 2 Yolo V8 Architecture

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C. Training Process

The training process is cantered around optimizing the YOLOv8 model parameters. The training process effectively minimized the loss function, demonstrating the model's convergence as illustrated in Fig. 3.

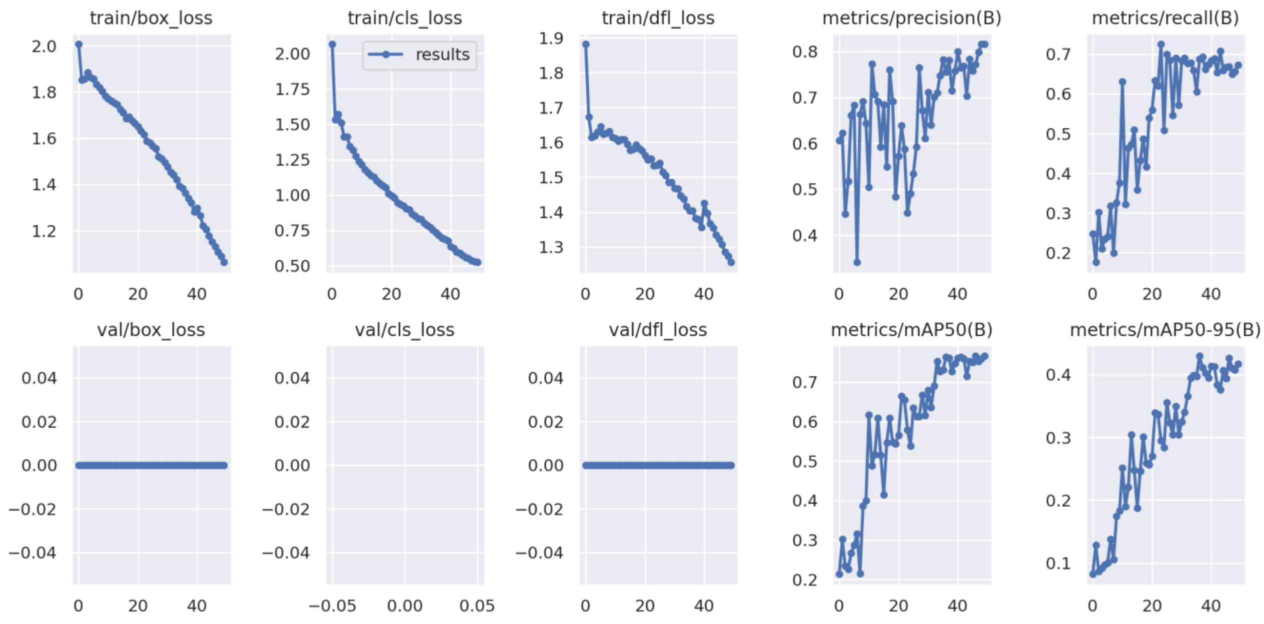

Fig. 3 Training Matrix

The loss function, comprising localization loss, confidence loss, and classification loss, is iteratively minimized over mini-batches of training data. This iterative optimization process enables the model to learn to accurately localize vehicles, assign confidence scores, and classify objects into predefined categories. During training, careful tuning of hyperparameters such as learning rate, batch size, and regularization techniques is conducted to optimize model convergence and prevent overfitting. Additionally, the training process is meticulously monitored using validation data to assess model performance and prevent over fitting, ensuring the model's generalizability across diverse traffic scenarios.

III. RESULTS AND DISCUSSION

The results section presents a detailed analysis of the performance and findings of the trained YOLOv8 model in vehicle detection and classification tasks. Wu et al. proposed Yolo v5-Ghost, an improved neural network structure, enhancing detection speed and reducing computational complexity for vehicle and distance detection in virtual environments [9]. Through rigorous experimentation and evaluation, the study aims to provide insights into the model's efficacy and limitations across diverse traffic scenarios.

The modifications made to enhance the YOLOv8 model, it is noteworthy to mention the work of Zhao et al. [10], who proposed a similar approach named YOLOv4_AF. Their model utilizes an attention mechanism to suppress interference features and incorporates modifications to the Feature Pyramid Network (FPN) part of the Path Aggregation Network (PAN) in order to improve object detection and classification performance. In the study by Baiat and Baydere [11] the potential of the YOLOv7 framework in enhancing traffic monitoring systems in smart cities is demonstrated.

A. Evaluation Metrics

The performance evaluation of the trained YOLOv8 model encompasses a comprehensive set of standard metrics, including, precision, recall and accuracy as shown in Table 2. These metrics serve as quantitative benchmarks to assess the model's accuracy, robustness, and generalization capabilities across diverse traffic scenarios and vehicle classes. Through meticulous analysis of these metrics, the study aims to quantify the model's performance and identify areas for improvement.

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TABLE II VEHICLE CLASSIFICATION PERFORMANCE

Class	Precision			Recall			Accuracy		
	YOLOv7	YOLOv5	Proposed	YOLOv7	YOLOv5	Proposed	YOLOv7	YOLOv5	Proposed
Motorcycle	87.4	82.3	**92.5**	83.4	81.3	**92.3**	87.2	81.6	**91.5**
Car	89.3	85.7	**93.5**	86.3	83.2	**90.1**	89.3	83.36	**94.6**
Van	85.7	81.6	**91.6**	82.7	79.8	**93.8**	87.6	84.7	**92.3**
Bus	86.1	85.2	**93.1**	83.1	78.7	**95.8**	83.2	81.9	**96.1**
truck	90.3	87.6	**95.5**	89.3	87.7	**95.9**	84.7	83.7	**98.7**

B. Experimental Findings

The experimental findings reveal the efficacy of the YOLOv8 model in accurately detecting and classifying vehicles in a wide range of traffic scenes. Quantitative analysis, underscores the model's proficiency in precisely localizing vehicles within bounding boxes, essential for tasks like traffic monitoring and management. Additionally, the study investigates the impact of various factors such as lighting conditions, weather, and traffic density on the model's performance to gain insights into its robustness and adaptability.

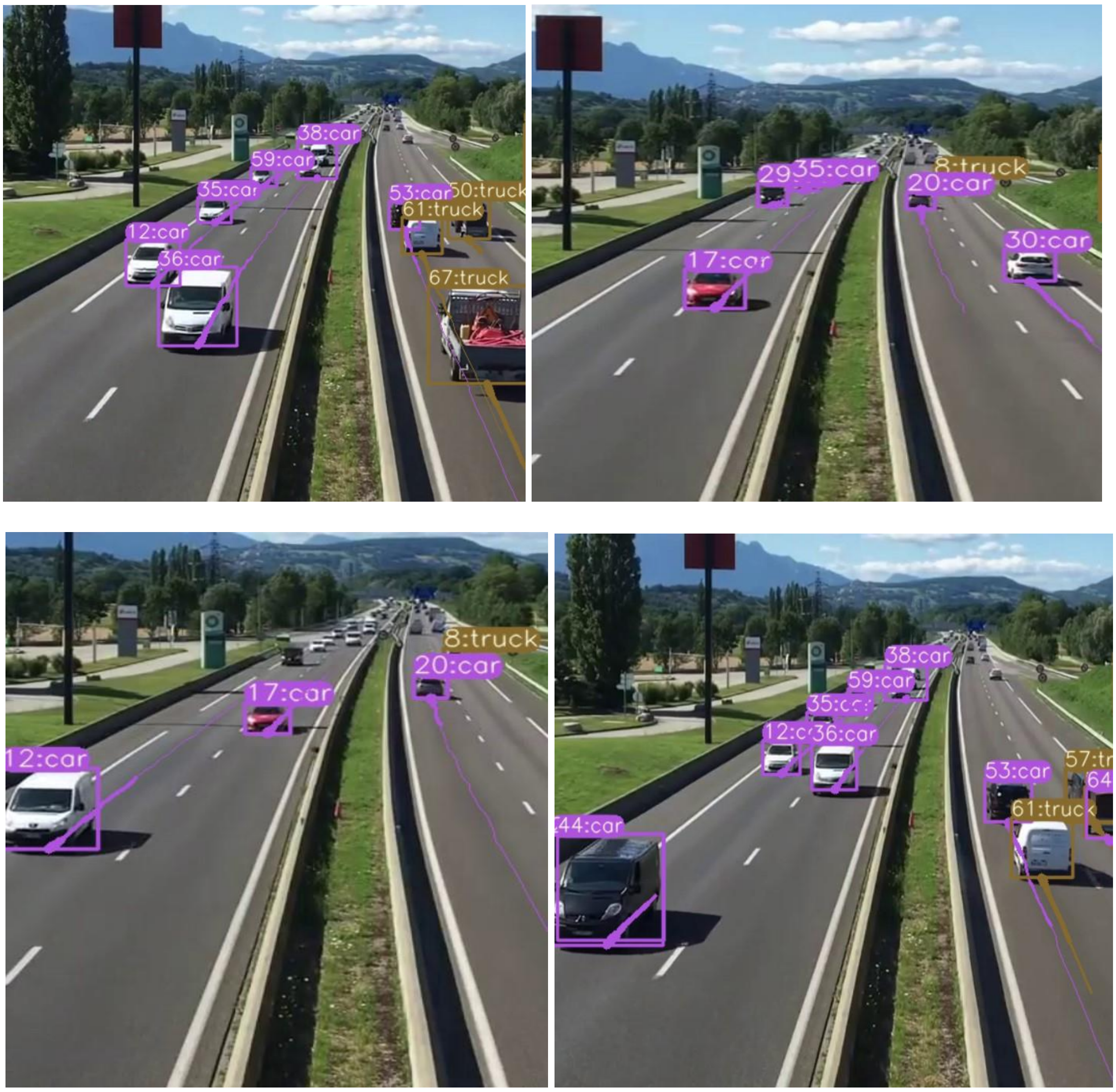

Fig. 4 Test result visualization

C. Qualitative Analysis

Qualitative analysis delves into the nuanced aspects of the detection outputs, offering insights into the model's performance under varying environmental conditions. By scrutinizing instances of false positives and false negatives, the study identifies areas for improvement, such as refining object classification algorithms and devising strategies to mitigate occlusion effects. This qualitative assessment provides valuable context to complement quantitative metrics, enhancing the understanding of the model's capabilities and limitations.

D. Model Optimization

The pursuit of model optimization involves a systematic exploration of techniques aimed at improving performance and efficiency. Hyperparameter tuning, encompassing adjustments to parameters like learning rate and batch size, is conducted to fine-tune the model's convergence behaviour and prevent overfitting.

Additionally, experimentation with different backbone architectures and post-processing methods, such as non-maximum suppression (NMS) and object tracking algorithms, is undertaken to refine detection results and streamline computational efficiency during inference. These optimization efforts are crucial for enhancing the model's practical utility and ensuring its efficacy in real-world applications. Xu et al. [12] addressed the challenge of vehicle detection in images by modifying YOLOv3 which includes increasing network depth and leveraging top-level feature maps.

This detailed examination of the evaluation metrics, experimental findings, qualitative analysis, and model optimization provides a comprehensive overview of the YOLOv8 model's performance in vehicle detection and classification tasks, laying the foundation for informed decision-making and further advancements in intelligent transportation systems.

IV. CONCLUSION

This work offers a comprehensive exploration of the YOLOv8 deep learning algorithm's efficacy in vehicle detection and classification within real-world traffic environments. Through meticulous dataset curation, model implementation, training, evaluation, and optimization, our research underscores the potential of deep learning techniques in addressing challenges inherent to intelligent transportation systems.

The experimental results highlight the YOLOv8 model's robustness and accuracy across diverse traffic scenarios, supported by both quantitative metrics like mean Average Precision (mAP) and Intersection over Union (IoU), and qualitative analyses of detection outputs. By delving into model optimization techniques, including hyperparameter tuning and post-processing methods, we achieve notable enhancements in performance metrics and computational efficiency. These findings not only contribute valuable insights into deep learning-based vehicle detection but also provide a solid foundation for practical applications in traffic management systems and autonomous vehicles.

Moving forward, future directions for the project include fine-tuning the YOLOv8 model for specific vehicle types, integrating the system into real-time applications, and exploring advanced tracking algorithms for improved accuracy. By bridging the gap between research and application, our work holds promise for revolutionizing transportation infrastructure, improving safety, and ushering in a new era of intelligent mobility solutions.

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