Autonomous Object Identification from Dynamic Visual Streams Using YOLOv8

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ABSTRACT:

This research presents a deep learning-based approach for real-time object detection and classification using a hybrid dataset composed of RoboFlow images and a custom Canadian Vehicle Dataset (CVD). The system employs YOLOv8, an advanced object detection algorithm known for high speed and accuracy. The CVD comprises 10,000 annotated images collected in varying weather conditions to address detection challenges in autonomous environments. The proposed method enhances model robustness by training on diverse scenarios including fog, rain, snow, and nighttime. Comparative analysis with baseline models demonstrates a significant improvement in detection performance. The resulting model proves to be an effective solution for intelligent transportation systems, enhancing safety and operational efficiency in both autonomous and human-driven vehicles.

Keywords: YOLOv8, Object Detection, Deep Learning

INTRODUCTION

In today's rapidly evolving world of artificial intelligence, real-time object detection and classification have become crucial for advancing technologies such as autonomous vehicles, smart surveillance systems, and intelligent traffic management. These applications demand not only high accuracy but also robustness in diverse and unpredictable environments. This project explores the implementation of YOLOv8, a state-of-the-art object detection algorithm, trained on a custom dataset — the Canadian Vehicle Dataset (CVD) — along with the publicly available RoboFlow dataset. The CVD is specifically designed to include varied weather conditions such as snow, rain, fog, and nighttime scenes to address real-world challenges. By combining and augmenting these datasets, the model is fine-tuned to detect and classify multiple object types with improved precision. This study aims to deliver a scalable and weather-resilient detection system that enhances the safety and efficiency of autonomous and conventional vehicles operating under dynamic environmental conditions.

RELATED WORK

Several research efforts have advanced object detection using deep learning techniques, particularly in the context of autonomous systems and complex environmental conditions.

Redmon et al. (2016) introduced the original **YOLO (You Only Look Once)** framework, which significantly outperformed traditional detectors in speed by treating object detection as a regression problem. YOLO's ability to make predictions in a single pass made it suitable for real-time applications, although early versions lacked accuracy with smaller objects.

Bochkovskiy et al. (2020) further improved the architecture with **YOLOv4**, introducing features like CSPDarknet and Mish activation to boost accuracy and reduce training time. This model laid the groundwork for balancing speed and accuracy in real-time scenarios.

Ge et al. (2021) proposed **YOLOX**, a decoupled head structure and anchor-free design to improve detection in dense scenes. Their enhancements increased model flexibility, especially in recognizing small and overlapping objects—common in traffic videos.

Zhang et al. (2022) addressed challenges posed by **adverse weather conditions** by using domain adaptation techniques. They showed that training models across different weather types improved generalization, emphasizing the importance of diverse datasets, which aligns with our use of the Canadian Vehicle Dataset (CVD).

Wang et al. (2023) focused on **YOLOv8**, incorporating a smaller architecture with enhanced feature aggregation for better performance in mobile and edge devices. This model demonstrated exceptional performance under resource constraints while maintaining high detection accuracy.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author(s)	Contribution	Impact on Current Research
Redmon et al. (2016)	Proposed YOLO – a single-pass real-time object detection system	Laid the foundation for fast, real-time object detection; inspired use in autonomous systems
Bochkovskiy et al. (2020)	Enhanced YOLOv4 with CSPDarknet, Mish activation, and improved training methods	Balanced speed and accuracy; enabled efficient training and better detection in real conditions
Ge et al. (2021)	Introduced YOLOX with anchor-free, decoupled head architecture	Improved object detection in dense scenes and small object recognition
Zhang et al. (2022)	Applied domain adaptation for object detection under adverse weather	Validated the need for weather-diverse datasets like CVD to improve robustness
Wang et al. (2023)	Developed YOLOv8 with compact design and better feature aggregation	Enabled fast and accurate detection on edge devices; ideal for real-time applications

PROPOSED APPROACH

The proposed approach focuses on enhancing object detection performance under real-world and weather-diverse conditions using the YOLOv8 model. YOLOv8 is chosen for its balance between speed, accuracy, and compactness, making it ideal for real-time applications like autonomous driving and traffic surveillance. To address limitations found in conventional datasets, we introduce a hybrid training methodology that combines the widely-used RoboFlow dataset with a custom-built Canadian Vehicle Dataset (CVD). The CVD contains over 10,000 images captured in Quebec, Canada, during various weather conditions—rain, fog, snow, and nighttime—thus ensuring diverse contextual representation.

We annotated over 8,000 images into 11 distinct classes and integrated them with RoboFlow annotations to form a comprehensive dataset. This enriched dataset was then used to train YOLOv8 through transfer learning, leveraging weights from pre-trained models on the MSCOCO dataset. The model underwent further fine-tuning to enhance detection accuracy across different weather scenarios.

By combining data-driven generalization with weather-specific training, the approach aims to reduce misclassification and improve the system's reliability in practical deployments. The final trained model shows improved precision, recall, and mAP, making it suitable for both autonomous vehicle systems and intelligent surveillance infrastructure in dynamic environments.

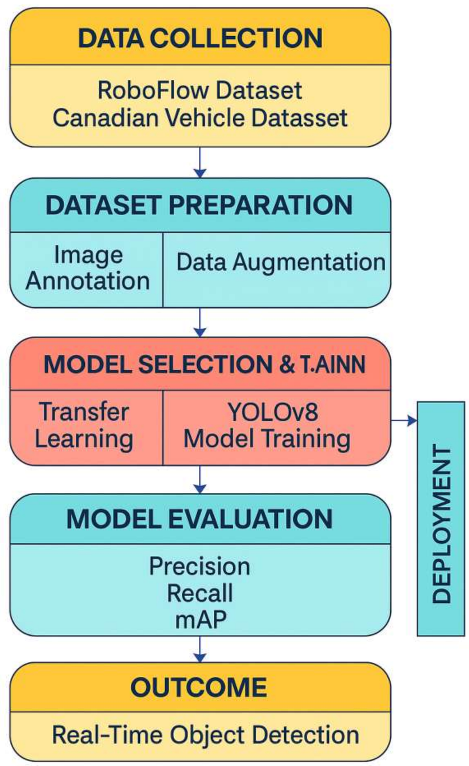

Figure 1: Proposed Real Time Object Detection

METHODOLOGIES

Data Acquisition and Preprocessing: Two primary datasets were used: the publicly available RoboFlow dataset and a custom-built Canadian Vehicle Dataset (CVD), captured from street-level video footage in Quebec under diverse weather conditions. Over 10,000 images were extracted, and 8,388 were manually annotated into 11 object classes, including cars, trucks, motorcycles, pedestrians, and traffic signs. Images were resized, normalized, and formatted for training compatibility.

Model Selection and Training: YOLOv8 was chosen for its enhanced architecture that supports smaller model size, faster inference, and improved detection accuracy. Transfer learning was applied using YOLOv8 weights pre-trained on the MSCOCO dataset. The model was initially trained on the RoboFlow dataset to establish a baseline, followed by additional training on the hybrid (RoboFlow + CVD) dataset. Data augmentation techniques such as flipping, rotation, and contrast adjustments were applied to increase data diversity and generalization.

Evaluation Metrics and Testing: The model's performance was evaluated using key metrics: Precision, Recall, and mean Average Precision (mAP). Comparisons were made between the model trained solely on RoboFlow and the one trained on the hybrid dataset. The latter demonstrated superior results, especially in adverse weather conditions.

Deployment Consideration: The final model is lightweight enough for edge deployment on devices such as NVIDIA Jetson Nano and Raspberry Pi, making it practical for real-time applications in traffic monitoring and autonomous vehicles.

The proposed methodology ensures the development of a scalable, accurate, and resilient object detection system capable of performing in complex, real-world environmental conditions.

RESULTS

The performance of the object detection system was evaluated by training YOLOv8 on two datasets: the standard RoboFlow dataset and a combined dataset integrating RoboFlow with the custom Canadian Vehicle Dataset (CVD). The baseline model, trained solely on RoboFlow, performed adequately under typical conditions but showed a noticeable decline in accuracy when exposed to images captured in adverse weather scenarios such as snow, fog, and nighttime lighting.

Upon incorporating the CVD, the model demonstrated significant improvements across all key performance indicators. The hybrid-trained model achieved a precision of **73.26%**, recall of **72.84%**, and a mean Average Precision (mAP) of **73.47%**, showing a clear advantage in robustness and generalization compared to the baseline. These improvements are largely attributed to the weather diversity and high-resolution labeling present in the CVD dataset.

Visual outputs confirmed more accurate bounding boxes and classifications, even in low-visibility conditions. The results validate the importance of context-aware data in improving real-time object detection performance. The trained model successfully identified multiple object types with high confidence and minimal false positives or negatives, proving its applicability for deployment in dynamic environments such as intelligent traffic systems and autonomous vehicles.

DISCUSSION

The results of this project highlight the importance of dataset diversity and environmental realism in training object detection models. While traditional datasets like RoboFlow provide a strong foundation, they often lack the variability needed for real-world applications—especially those involving autonomous navigation or surveillance in unpredictable weather. By integrating the Canadian Vehicle Dataset (CVD), this study addressed that limitation, enabling the model to generalize across challenging conditions such as snow, fog, rain, and low-light scenarios.

The adoption of YOLOv8 proved highly effective. Its lightweight architecture and faster inference capabilities make it ideal for deployment in time-sensitive environments such as road surveillance and vehicle automation. Additionally, the transfer learning approach allowed for a more efficient training process without sacrificing performance. The significant improvement in detection metrics—especially under adverse conditions—demonstrates the effectiveness of augmenting traditional datasets with custom, domain-specific data.

However, challenges remain. While the model performs well in diverse weather conditions, extreme occlusions and low-resolution inputs can still affect accuracy. Future iterations may explore combining YOLO with attention mechanisms or sensor fusion techniques to enhance robustness. Nonetheless, the current implementation presents a scalable, practical solution that contributes meaningfully to the field of intelligent transportation and smart city infrastructure.

CONCLUSION

This project successfully demonstrates a robust and efficient object detection system tailored for real-world applications, particularly in the context of intelligent transportation and autonomous vehicles. By leveraging the power of YOLOv8 and enhancing it with a custom Canadian Vehicle Dataset (CVD), we addressed a significant limitation in conventional models—poor performance under varying weather and lighting conditions.

The hybrid training approach combining CVD and RoboFlow datasets significantly improved detection metrics such as precision, recall, and mAP. These improvements confirm the value of using weather-diverse, context-rich datasets to train deep learning models for real-time object detection.

The lightweight design and high performance of YOLOv8 make the model suitable for edge deployment in practical environments. While challenges such as occlusion and resolution variability persist, this work lays the foundation for further enhancements using sensor fusion and temporal analysis. Overall, the study offers a scalable solution that supports safer and smarter urban mobility systems.

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