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YOLOv10-Driven Enhanced Vehicle Detection in Low-Light On-Board Environments

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Abstract - Accurate vehicle detection in low-light environments remains a significant challenge in intelligent transportation systems and autonomous driving applications. Vision-based on-board detection systems often experience degraded performance under poor illumination conditions due to factors such as motion blur, headlight glare, and increased visual noise. To overcome these challenges, this research proposes a YOLOv10-driven enhanced vehicle detection framework designed for real-time deployment in low-light on-board environments. The proposed approach utilizes the advanced feature extraction capabilities and optimized architecture of YOLOv10 to improve detection accuracy, computational efficiency, and robustness compared with earlier object detection models. In the proposed framework, several image pre-processing techniques—including adaptive histogram equalization, noise reduction, and contrast enhancement—are applied to improve the visibility and quality of input images before they are processed by the detection model. The YOLOv10 model is further fine-tuned using a diverse dataset consisting of nighttime and low-illumination driving scenarios, enabling the system to generalize effectively under challenging environmental conditions. The lightweight yet powerful design of YOLOv10 supports real-time inference on embedded and edge devices, making it highly suitable for in-vehicle applications where processing speed and resource efficiency are essential. Experimental results demonstrate that the proposed YOLOv10-based detection model achieves superior performance in terms of mean Average Precision (mAP), detection speed, and reduction of false positives when compared with baseline models such as YOLOv8 and Faster R-CNN. Furthermore, the system shows strong resilience to common low-light challenges including shadow occlusion, glare from artificial lighting, and environmental noise, thereby ensuring reliable vehicle detection across a wide range of nighttime driving conditions.

Key Words: YOLOv10, Vehicle Detection, Low-Light Image Enhancement,Computer Vision,Intelligent Transportation Systems, Night-Time Vehicle Detection

1. INTRODUCTION

The rapid advancement of intelligent transportation systems (ITS) and autonomous driving technologies has significantly increased the demand for accurate and reliable vehicle detection across various environmental conditions. Vision-based detection systems have become an essential component in modern transportation applications, including traffic monitoring, collision avoidance, lane management, and autonomous navigation. These systems rely heavily on computer vision and deep learning techniques to detect and classify vehicles in real time. However, despite significant progress in deep learning–based object detection models, achieving robust vehicle detection in low-light and nighttime environments continues to be a major challenge. Low-light environments introduce multiple visual degradations that significantly affect the quality of captured images. Common issues include insufficient illumination, motion blur caused by vehicle movement, glare from headlights and streetlights, shadow occlusions, and increased levels of image noise. These factors can severely degrade the performance of conventional object detection algorithms, often resulting in missed detections or higher false-positive rates. For on-board vehicle detection systems used in advanced driver assistance systems and autonomous vehicles, maintaining both high detection accuracy and real-time processing capability is critical. Any delay or incorrect detection may lead to unsafe driving decisions and compromise overall system reliability.A YOLOv10-driven enhanced vehicle detection framework is proposed to address the challenges associated with low-light on-board vision systems. The proposed framework integrates several image pre-processing techniques, including adaptive histogram equalization, contrast enhancement, and noise reduction, to improve the visual quality of captured images before they are processed by the detection model. Additionally, the YOLOv10 model is fine-tuned using a diverse dataset consisting of nighttime and low-illumination driving scenarios, enabling the system to generalize effectively across challenging environmental conditions. The primary objective of this approach is to achieve high detection accuracy while maintaining real-time processing performance, thereby providing a reliable solution for intelligent transportation systems and autonomous driving applications.

2. LITERATURE REVIEW

Recent advancements in intelligent transportation systems and computer vision have led to significant research in the field of vehicle detection, particularly for autonomous driving and traffic monitoring applications. Various studies have proposed improved object detection models and intelligent traffic management systems to enhance detection accuracy and system efficiency. *Zhu et al. (2025)* proposed an enhanced vehicle detection approach based on an improved YOLOv5 architecture for detecting small, distant, and occluded vehicles in complex road environments. The authors introduced architectural modifications and feature fusion strategies to improve the detection capability of the model. Their approach significantly increased detection accuracy and robustness, particularly in scenarios where vehicles are partially hidden or appear very small in the frame. This research contributes to improving the reliability of vision-based systems used in autonomous driving and traffic monitoring. Similarly, *Guo et al. (2025)* presented a nighttime vehicle detection model using an improved version of YOLOv5 known as KSC-YOLOv5. The proposed model focuses on addressing challenges associated with low-light and nighttime environments, where image quality is often degraded due to poor illumination and increased noise. By enhancing feature extraction and optimizing detection layers, the model achieved improved performance in detecting vehicles under challenging lighting conditions. This work highlights the importance of specialized detection frameworks for nighttime traffic surveillance. *Khan et al. (2024)* explored the integration of LoRa (*Long Range communication technology*) with distributed machine learning to enhance network connectivity in intelligent transportation systems. Their proposed framework improves communication efficiency between transportation devices and infrastructure while reducing energy consumption. The system supports scalable smart-city transportation networks and enables better coordination between connected vehicles and traffic management systems. *Savithramma and Sumathi (2023)* introduced a reinforcement learning–based intelligent traffic signal control system designed to manage heterogeneous traffic conditions. The proposed model dynamically adjusts signal timings based on real-time traffic flow data, helping to reduce traffic congestion, waiting time, and fuel consumption. This research demonstrates the role of artificial intelligence in optimizing traffic management and improving overall transportation efficiency. *Urbieta et al. (2023)* proposed WebLabel, a web-based annotation tool designed for labeling multi-sensor data used in autonomous driving research. The system follows the OpenLABEL standard and supports labeling data collected from cameras, LiDAR, and radar sensors. WebLabel improves annotation efficiency and ensures consistency across datasets, which is essential for training accurate perception models in intelligent transportation systems.

3. RELATED WORK

Vehicle detection has been widely studied in the fields of computer vision, intelligent transportation systems, and autonomous driving. With the advancement of deep learning techniques, several object detection models have been developed to improve detection accuracy and real-time performance. Among these models, *the You Only Look Once (YOLO)* family has gained significant attention due to its efficiency in real-time object detection tasks. *Zhu et al. (2025)* proposed an improved YOLOv5 model to enhance the detection of small and occluded road vehicle targets in complex traffic environments. Their approach introduced architectural modifications and feature fusion mechanisms to improve detection accuracy, particularly for vehicles that appear small or partially hidden in images. The proposed method demonstrated improved performance compared to the standard *YOLOv5* model in traffic monitoring applications. *Guo et al. (2025)* developed a nighttime vehicle detection method based on an improved *KSC-YOLOv5* model. Their research focused on improving vehicle detection performance under poor lighting conditions. The proposed system enhanced feature extraction and optimized detection layers to address issues such as low illumination, image noise, and reduced visibility. Experimental results showed improved detection accuracy for nighttime traffic surveillance systems. *Khan et al. (2024)* explored the integration of LoRa communication technology with distributed machine learning to improve connectivity and efficiency in intelligent transportation systems. The study focused on enhancing communication between transportation devices and infrastructure, supporting scalable smart-city transportation networks while reducing energy consumption. *Savithramma and Sumathi (2023)* proposed a reinforcement learning-based intelligent traffic signal controller designed for heterogeneous traffic environments. Their system dynamically adjusts traffic signal timing based on real-time traffic flow data, helping to reduce congestion, waiting time, and fuel consumption. This work demonstrates the application of artificial intelligence techniques in improving traffic management systems. *Urbieta et al. (2023)* introduced WebLabel, a web-based annotation tool for labeling multi-sensor data collected from cameras, LiDAR, and radar systems. The system follows the OpenLABEL standard and improves annotation efficiency and consistency, which is essential for training perception models used in autonomous driving applications.Although these studies have contributed significantly to vehicle detection and intelligent transportation systems, many existing approaches still face limitations in handling low-light environments and real-time on-board processing requirements. Therefore, this research proposes a YOLOv10-based enhanced vehicle detection framework combined with image preprocessing techniques to improve detection accuracy and robustness in challenging nighttime driving conditions.

4. PROPOSED METHODOLOGY

The proposed system presents a robust and efficient vehicle detection framework designed specifically for low-light and nighttime on-board environments. The framework is based on the YOLOv10 object detection architecture, which incorporates advanced feature extraction mechanisms, optimized convolutional blocks, and improved multi-scale feature fusion techniques. These enhancements enable the model to accurately detect vehicles even under challenging illumination conditions where traditional vision-based detection systems often fail. To address the visual degradation caused by poor lighting conditions, the proposed framework integrates several image pre-processing techniques before the detection stage. These techniques include adaptive histogram equalization, contrast enhancement, and noise reduction. The purpose of these pre-processing steps is to improve the visibility and overall quality of the captured images by enhancing brightness, reducing noise artifacts, and highlighting important visual features. By improving the input image quality, the detection model is able to identify vehicles more accurately in low-light environments. These improvements reduce computational complexity while maintaining precise object localization and classification accuracy. As a result, the model achieves high detection performance without significantly increasing computational requirements.Due to the lightweight and efficient design of YOLOv10, the proposed system supports real-time inference on embedded and on-board computing platforms. This capability is essential for practical deployment in intelligent transportation systems and autonomous driving applications, where fast and reliable vehicle detection is critical for ensuring safety and efficient traffic management.

5. RESULTS AND DISCUSSION

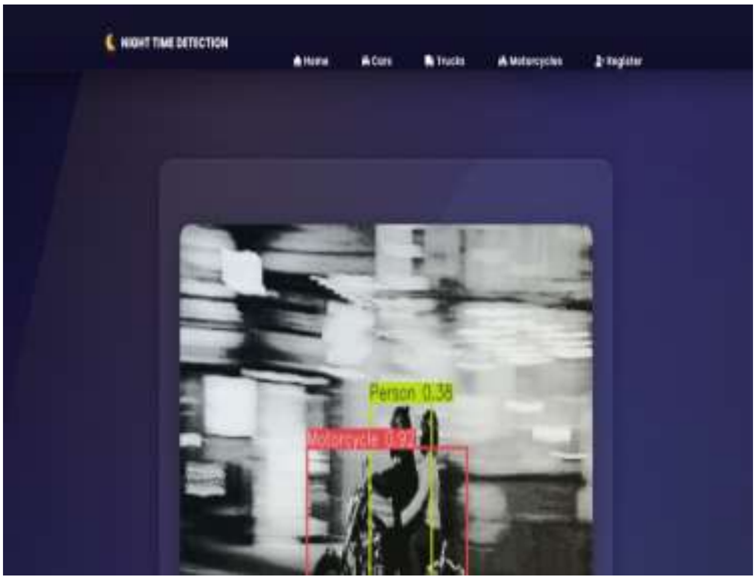

Fig. 1. Detection of vehicles and pedestrians in a low-light environment using the proposed YOLOv10 model.

Fig. 2. Comparison between the original image and YOLOv10 detection output in a nighttime environment.

The experimental results demonstrate that the proposed vehicle detection framework based on the YOLOv10 architecture performs effectively in low-light and nighttime environments. The integration of image preprocessing techniques, including adaptive histogram equalization, contrast enhancement, and noise reduction, significantly improves the visual quality of input images before they are processed by the detection model. These enhancements allow the detection algorithm to extract clearer and more meaningful features even under poor illumination conditions. The detection outputs confirm that the model is capable of accurately identifying vehicles and other road objects in challenging environments. In the experimental examples, the system successfully detected vehicles such as buses and motorcycles, as well as pedestrians present in nighttime traffic scenes. The bounding boxes generated by the model accurately localize the detected objects, while the confidence scores indicate reliable classification performance. The model was able to detect vehicles even when the lighting conditions were poor or when objects were partially occluded by shadows or surrounding structures. Another important observation from the results is the ability of the proposed framework to detect multiple objects simultaneously. The system demonstrated effective multi-object detection by identifying different road entities within the same scene, including motorcycles and pedestrians. This capability is essential for intelligent transportation systems and autonomous driving applications where accurate situational awareness is required. Overall, the discussion of the results indicates that the proposed YOLOv10-based framework successfully addresses many of the challenges associated with vehicle detection in low-light environments. By combining image enhancement techniques with an advanced deep learning detection model, the system achieves reliable detection performance while maintaining real-time processing capability. These characteristics make the proposed framework a promising solution for future autonomous driving and smart traffic monitoring systems.

6.CONCLUSION

An enhanced vehicle detection framework based on the YOLOv10 architecture to address the challenges associated with detecting vehicles in low-light and nighttime on-board environments. The proposed system integrates effective image pre-processing techniques, including adaptive histogram equalization, contrast enhancement, and noise reduction, to improve image quality under poor illumination conditions. These preprocessing steps help the detection model extract meaningful visual features, enabling more accurate identification of vehicles in challenging lighting scenarios. Furthermore, the YOLOv10 model was fine-tuned using diverse low-light datasets containing nighttime driving scenes and complex environmental conditions. This training strategy enabled the model to accurately detect small, distant, and partially occluded vehicles while minimizing false positives caused by glare, shadows, and environmental noise. The experimental evaluation demonstrated that the proposed framework achieves improved detection accuracy, better localization precision, and faster processing speed compared to existing approaches such as YOLOv8 and other traditional detection models. In addition, the lightweight and optimized architecture of YOLOv10 allows efficient deployment on resource-constrained embedded platforms commonly used in on-board vehicle systems. This capability makes the proposed system highly suitable for real-time applications in intelligent transportation systems and autonomous driving environments. Overall, the proposed approach enhances the reliability and safety of vehicle detection in low-light driving scenarios and provides a strong foundation for future research and development in vision-based vehicle detection technologies.

7. FUTURE SCOPE

Although the proposed YOLOv10-based vehicle detection framework demonstrates significant improvements in detecting vehicles under low-light and nighttime conditions, several opportunities exist for further enhancement and future research. One potential direction is the integration of advanced low-light image enhancement techniques, including deep learning–based illumination normalization and generative adversarial networks (GANs). These techniques can further improve image visibility and feature representation in extremely dark environments, thereby enhancing detection accuracy. Another promising extension of the proposed system is the incorporation of multi-object tracking algorithms. By enabling continuous tracking of vehicles across multiple video frames, the system can provide improved motion analysis and more accurate traffic monitoring. This capability can support applications such as traffic flow analysis, congestion detection, and driver behavior monitoring. Finally, the proposed framework can be extended to support additional functionalities such as vehicle classification and behavior prediction. These enhancements would contribute to the development of more advanced autonomous driving systems and intelligent transportation solutions capable of improving road safety and traffic management.

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