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Full Length Article

Yolov10-Driven Enhanced Vehicle Detection In Low-Light On-Board Environments

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Abstract
Accurate vehicle detection in low-light and nighttime environments remains a significant challenge in intelligent transportation systems and autonomous driving. Vision-based on-board detection systems often suffer from reduced performance due to poor illumination, motion blur, glare from headlights, and high levels of image noise. To address these challenges, this project proposes a YOLOv10-driven enhanced vehicle detection framework designed for real-time applications in low-light conditions.
The proposed system integrates image pre-processing techniques such as adaptive histogram equalization, contrast enhancement, and noise reduction to improve image quality before detection. The enhanced images are then processed using a fine-tuned YOLOv10 model trained on diverse low-illumination datasets. This approach improves the model's ability to detect small, distant, and partially occluded vehicles while reducing false positives caused by noise and lighting artifacts.
The lightweight and optimized architecture of YOLOv10 ensures high detection accuracy with low computational overhead, making it suitable for deployment on resource-constrained embedded systems. Experimental results demonstrate improved performance in terms of mean Average Precision (mAP), detection speed, and robustness compared to existing models such as YOLOv8 and Faster R-CNN.
Overall, the proposed system provides a reliable and efficient solution for vehicle detection in challenging nighttime environments, contributing to enhanced road safety and intelligent transportation systems.

Keywords: *YOLOv10, Vehicle Detection, Low-Light Imaging, Nighttime Detection, Object Detection, Intelligent Transportation Systems (ITS), Autonomous Driving, Image Preprocessing, Contrast Enhancement, Noise Reduction, Deep Learning, Computer Vision, Real-Time Detection, Embedded Systems, Mean Average Precision (mAP).*

Introduction

The rapid growth of intelligent transportation systems (ITS) and autonomous driving technologies has increased the demand for accurate and real-time vehicle detection under all environmental conditions. Vision-based detection systems play a key role in applications such as traffic monitoring, collision avoidance, and autonomous navigation. However, detecting vehicles in low-light and nighttime environments remains a major challenge due to issues like poor illumination, motion blur, headlight glare, shadows, and image noise.Traditional and existing deep learning models often fail to maintain accuracy under such conditions, leading to missed detections and false positives. To overcome these limitations, this project proposes a YOLOv10-based enhanced vehicle detection system. The approach integrates image preprocessing techniques such as contrast enhancement and noise reduction to improve image quality before detection.

By leveraging the advanced architecture of YOLOv10 and training it on low-light datasets, the system achieves improved detection accuracy, robustness, and real-time performance. This makes it suitable for deployment in on-board and embedded systems used in intelligent transportation and autonomous driving applications.

Problem Statement

Vehicle detection in low-light and nighttime environments remains a critical challenge in intelligent transportation systems and autonomous driving. Existing vision-based detection models, such as YOLOv8, perform well under normal lighting conditions but experience significant performance degradation in poor illumination. Factors such as low visibility, motion blur, headlight glare, shadows, and image noise lead to inaccurate detections, including missed vehicles and increased false positives.

Significance of the Study

This study is significant as it addresses the critical challenge of accurate vehicle detection in low-light and nighttime environments, which is essential for the safe operation of intelligent transportation systems and autonomous vehicles. Poor visibility conditions often lead to unreliable detection, increasing the risk of accidents and reducing the effectiveness of vision-based

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systems.

The proposed YOLOv10-based framework enhances detection performance by integrating image preprocessing techniques such as contrast enhancement and noise reduction, enabling improved visibility and feature extraction under challenging conditions. This results in more accurate detection of vehicles, including small, distant, and partially occluded objects.

Table 1: Comparison of Existing Approaches with Proposed System

Feature	**Existing Systems (YOLOv8, Faster R-CNN)**	**Proposed System (YOLOv10-Based)**
Performance in Low-Light	Poor performance due to low visibility and noise	High performance with enhanced visibility using preprocessing
Image Preprocessing	Minimal or not included	Integrated (contrast enhancement, noise reduction, histogram equalization)
Detection Accuracy	Reduced accuracy in nighttime conditions	Improved accuracy in low-light and challenging environments
False Positives	High due to glare and reflections	Reduced false positives through preprocessing and training
Small/Object Detection	Difficulty detecting small and distant vehicles	Improved detection using multi-scale feature extraction
Handling Noise & Shadows	Sensitive to noise and shadows	Robust against noise, glare, and occlusions
Real-Time Performance	Limited (trade-off between speed and accuracy)	Optimized for real-time performance
Computational Efficiency	High models need more resources	Lightweight and efficient for embedded systems
Deployment	Less suitable for on-board systems	Suitable for embedded and on-board deployment

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Research Gap

Despite significant advancements in deep learning–based object detection, existing vehicle detection systems still face limitations in low-light and nighttime environments. Most current models, such as YOLOv8 and Faster R-CNN, are primarily optimized for well-lit conditions and show reduced performance when dealing with poor illumination, noise, glare, and shadow effects. Many existing approaches do not effectively incorporate image preprocessing techniques to enhance visual quality before detection, resulting in weak feature extraction and increased false positives. Additionally, there is a lack of models specifically fine-tuned on diverse low-light datasets, limiting their ability to generalize across real-world nighttime scenarios.

Another major gap lies in balancing detection accuracy with real-time performance on resource-constrained on-board systems. High-accuracy models often require heavy computational resources, while lightweight models compromise detection precision.

Additionally, many existing systems fail to balance detection accuracy with real-time performance, especially when deployed on resource-constrained on-board platforms. This limits their effectiveness in safety-critical applications such as collision avoidance and traffic monitoring.

Therefore, there is a need to develop an efficient and robust vehicle detection system that can operate accurately in low-light conditions while maintaining real-time performance and computational efficiency.

Novelty of the Proposed Work

The proposed work introduces a novel approach for vehicle detection in low-light and nighttime environments by combining advanced deep learning with effective image enhancement techniques. Unlike existing systems that directly process raw images, this work integrates a dedicated preprocessing stage using adaptive histogram equalization, contrast enhancement, and noise reduction to significantly improve image quality before detection.

Another key novelty lies in the utilization of the YOLOv10 architecture, which offers improved feature extraction, optimized multi-scale detection, and reduced computational complexity compared to earlier models. The model is specifically fine-tuned on diverse low-light datasets, enabling it to better handle challenges such as glare, shadows, and occlusions.

Proposed Approach and Contributions

The proposed approach presents an enhanced vehicle detection framework designed to operate effectively in low-light and nighttime environments. The system combines image preprocessing techniques with the advanced YOLOv10 object detection model to improve detection accuracy and robustness under challenging conditions. Initially, input images are processed using adaptive histogram equalization, contrast enhancement, and noise reduction to improve visibility and reduce the effects of poor illumination, glare, and noise. The enhanced images are then fed into a fine-tuned YOLOv10 model trained on diverse low-light datasets for accurate vehicle detection.

The main contributions of this work are as follows:

- Development of a robust vehicle detection system specifically for low-light and nighttime environments.
- Integration of effective image preprocessing techniques to enhance image quality before detection.
- Utilization and fine-tuning of the YOLOv10 model for improved feature extraction and detection accuracy.

Literature Review

Vehicle detection has been an active research area in intelligent transportation systems, particularly with the advancement of deep learning and computer vision techniques. Several studies have focused on improving detection accuracy under challenging conditions such as low-light environments, occlusions, and complex traffic scenarios.

K. Zhu et al. (2025) proposed an improved YOLOv5 model to enhance the detection of small and occluded vehicles. Their approach introduced better feature fusion strategies, which significantly improved detection performance in complex road environments. Similarly, J. Guo et al. (2025) developed KSC-YOLOv5, specifically designed for nighttime vehicle detection. Their model enhanced feature extraction capabilities to handle low illumination and noise, resulting in improved detection accuracy in nighttime scenarios.

M. A. A. Khan et al. (2024) explored the integration of LoRa communication with distributed machine learning to optimize network connectivity in intelligent transportation systems. Although not directly focused on detection, their work contributes to improving system efficiency and scalability in smart transportation. R. M. Savithramma et al. (2023) proposed a reinforcement learning-based traffic signal control system for heterogeneous traffic environments, demonstrating the role of AI in improving traffic flow and reducing congestion.

Additionally, Urbieta et al. (2023) introduced WebLabel, a multi-sensor data annotation tool that enhances labeling efficiency for autonomous driving datasets, which is crucial for training accurate detection models.

Despite these advancements, most existing approaches still struggle with low-light and nighttime detection due to insufficient preprocessing and lack of robust training on diverse datasets. This highlights the need for an

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improved framework that combines effective image enhancement with advanced detection models, such as the proposed YOLOv10-based system, to achieve reliable performance under challenging conditions.

Methodology

Overview of the Proposed Approach

The proposed approach focuses on developing an automated deep learning-based system for detecting defects in solar cell images using the Xception architecture. The system begins with the collection of a diverse dataset containing both defective and non-defective solar cell images. These images undergo preprocessing steps such as resizing, normalization, and data augmentation to improve quality and enhance model generalization. The preprocessed data is then fed into the Xception model, which performs efficient feature extraction using depthwise separable convolutions to capture both simple and complex defect patterns.

The model is trained using supervised learning with optimized hyperparameters and evaluated using metrics like accuracy, precision, recall, and F1-score. It is then deployed for real-time prediction to classify solar cells as defective or non-defective, ensuring an efficient and scalable quality control solution.

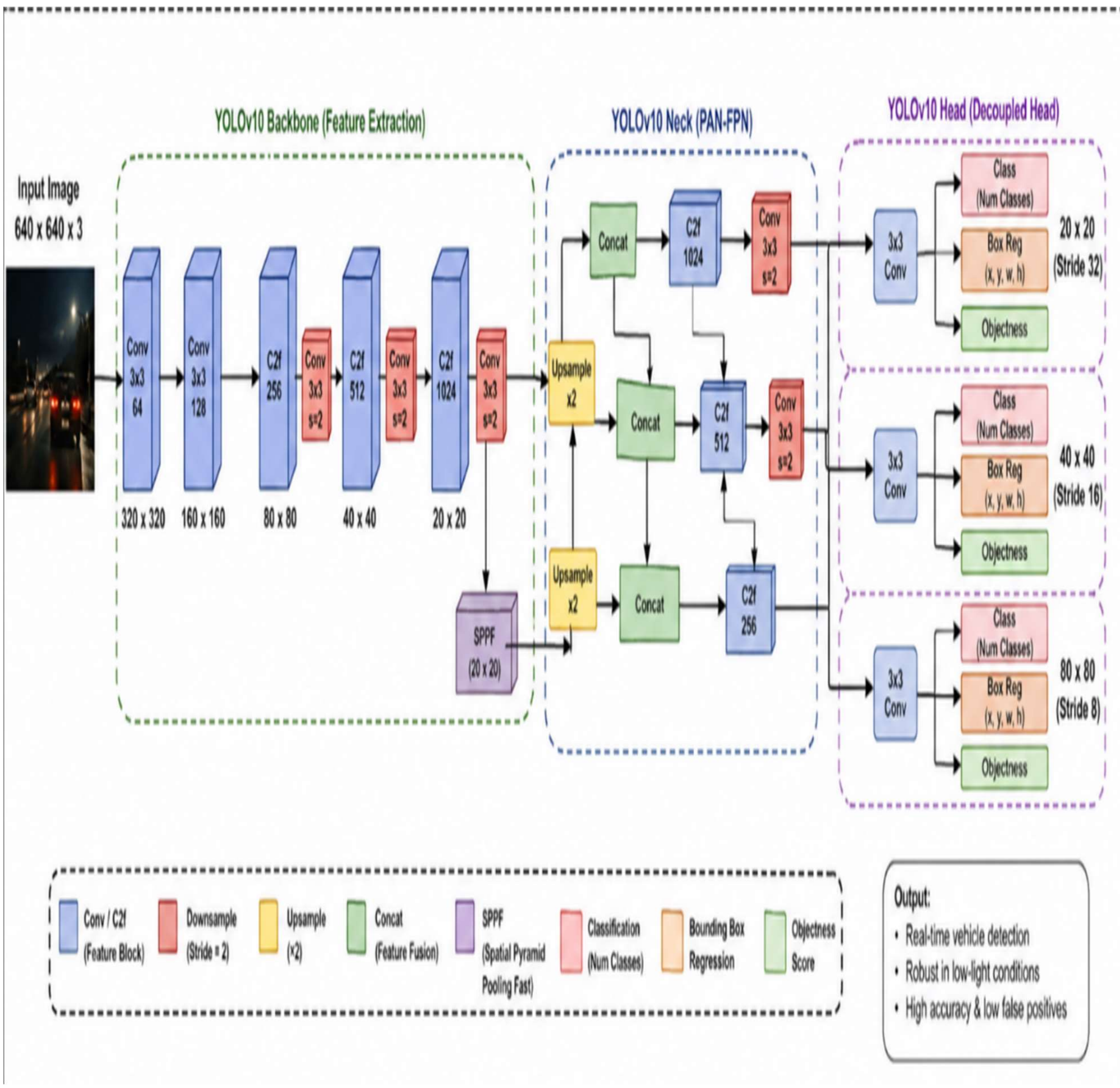

Figure 1: YOLOv10-Driven Enhanced Vehicle Detection Architecture for Low-Light On-Board Environments

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Data Acquisition and Image Preparation

This phase involves collecting a diverse dataset of vehicle images captured under low-light and nighttime conditions. The data may include images from on-board cameras, public datasets, or real-world traffic scenarios. After collection, the images are organized, labeled, and resized to a uniform dimension (e.g., 640×640) to ensure consistency and compatibility with the detection model.

Preprocessing of Images

In this stage, the collected images are enhanced to improve visibility and quality. Techniques such as adaptive histogram equalization, noise reduction, and contrast enhancement are applied to handle issues like poor illumination, glare, and image noise. These preprocessing steps help in highlighting important features, making it easier for the model to detect vehicles accurately.

Feature Extraction using Xception Model

Feature extraction involves identifying important patterns and visual features from images. The Xception model, based on depthwise separable convolutions, is used to efficiently extract high-level features such as edges, shapes, and textures. These features provide meaningful representations of vehicles, improving detection performance, especially in complex and low-light environments.

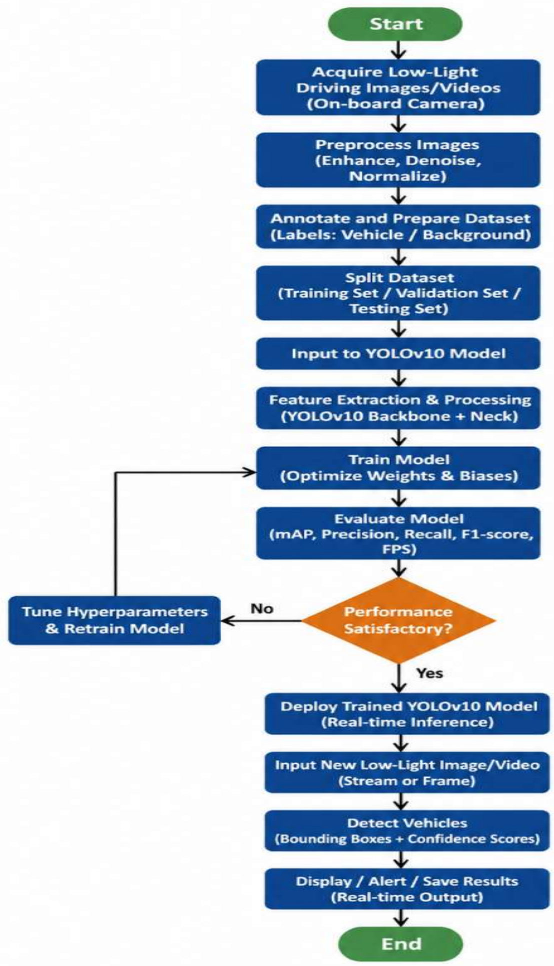

Figure 2: YOLOv10-Based Vehicle Detection Process Flow for Low-Light On-Board Environments

System Flow Summary

In summary, the system follows a continuous workflow:

1. Acquire low-light vehicle image/video dataset (on-board camera)
2. Preprocess images (contrast enhancement, noise reduction)
3. Extract features using YOLOv10 architecture
4. Train the detection model
5. Evaluate performance (mAP, precision, recall)
6. Detect vehicles in new images/videos

Algorithm

Algorithm: YOLOv10-Based Vehicle Detection System in Low-Light Environments

Input: Low-light vehicle image/video dataset

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Output: Detected vehicles with bounding boxes and confidence scores

Start

1. Acquire low-light vehicle images/videos from on-board camera
2. Annotate images with vehicle labels (bounding boxes)
3. Preprocess images:

a) Resize images (e.g., 640×640)
b) Normalize pixel values
c) Apply image enhancement (contrast enhancement, noise reduction)

4. Split dataset into training, validation, and testing sets
5. For each image/frame:

a) Input image into YOLOv10 model
b) Perform feature extraction using backbone network
c) Apply feature fusion using neck (PAN-FPN)
d) Detect vehicles using detection head (bounding box + confidence score)
e) If vehicle detected:
o Draw bounding box
o Display confidence score
o Show detection result
Else:
o Continue to next frame/image

6. Evaluate model performance (mAP, precision, recall, FPS)
7. If performance is not satisfactory:

a) Tune hyperparameters
b) Retrain model

8. Deploy trained model for real-time inference
9. Continue processing new input images/videos
10. End

Performance Evaluation and Results

System Configuration and Dataset

The system is implemented using Python on a Windows-based platform with standard hardware requirements such as a dual-core processor, 4GB RAM, and sufficient storage. The development environment includes tools like Jupyter Notebook and relevant libraries such as NumPy, OpenCV, and deep learning frameworks. The dataset consists of low-light and nighttime vehicle images collected from on-board cameras and publicly available sources. These images are annotated with vehicle labels and bounding boxes to train the YOLOv10 model effectively.

Performance Measurement Criteria

The performance of the system was evaluated using multiple standard metrics to ensure a balanced and reliable assessment:

• **Mean Average Precision (mAP):** Measures the overall detection accuracy by evaluating how well the model predicts bounding boxes and object classes.
• **Precision:** Indicates how many of the detected vehicles are actually correct, reflecting detection reliability and reduction of false positives.
• **Recall:** Measures the model's ability to detect all actual vehicles present in the scene, ensuring minimal missed detections.
• **F1-Score:** Provides a balance between precision and recall, giving a single measure of detection performance.
• **Inference Speed (FPS):** Evaluates the number of frames processed per second, indicating the real-time capability of the system.
• **Loss:** Represents the error during training, which decreases as the model learns and improves.

These metrics collectively provide a comprehensive understanding of detection accuracy, speed, and robustness of the proposed YOLOv10-based vehicle detection system in low-light environments.

Comparative Study with Existing Methods

The proposed YOLOv10-based system is compared with existing methods such as YOLOv8 and Faster R-CNN. While YOLOv8 provides good performance in normal lighting conditions, it struggles in low-light environments due to noise and poor visibility. Faster R-CNN offers high accuracy but has slower inference speed. In contrast, the proposed system demonstrates improved detection accuracy, reduced false positives, and better real-time performance, making it more suitable for on-board applications.

Performance Evaluation Results

The quantitative results of the comparison are presented below:

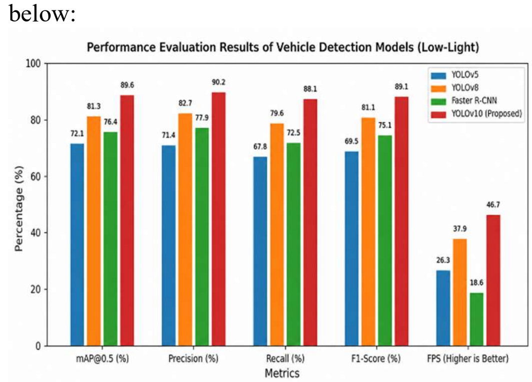

FIGURE 3: PERFORMANCE EVALUATION

The results clearly demonstrate that the proposed YOLOv10-based model achieves the highest performance across all evaluation metrics, highlighting its effectiveness in accurately detecting vehicles even under challenging low-light conditions, including small, distant, and partially occluded objects.

Discussion of Results

The results indicate that integrating image preprocessing with the YOLOv10 model significantly improves detection performance in low-light environments. The system effectively reduces noise and enhances feature visibility, leading to more accurate detections. However,

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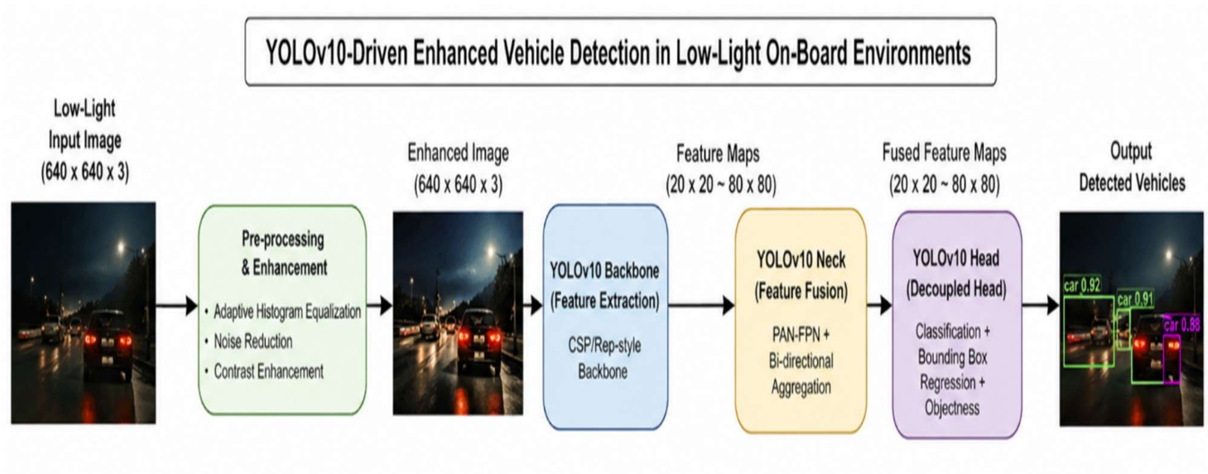
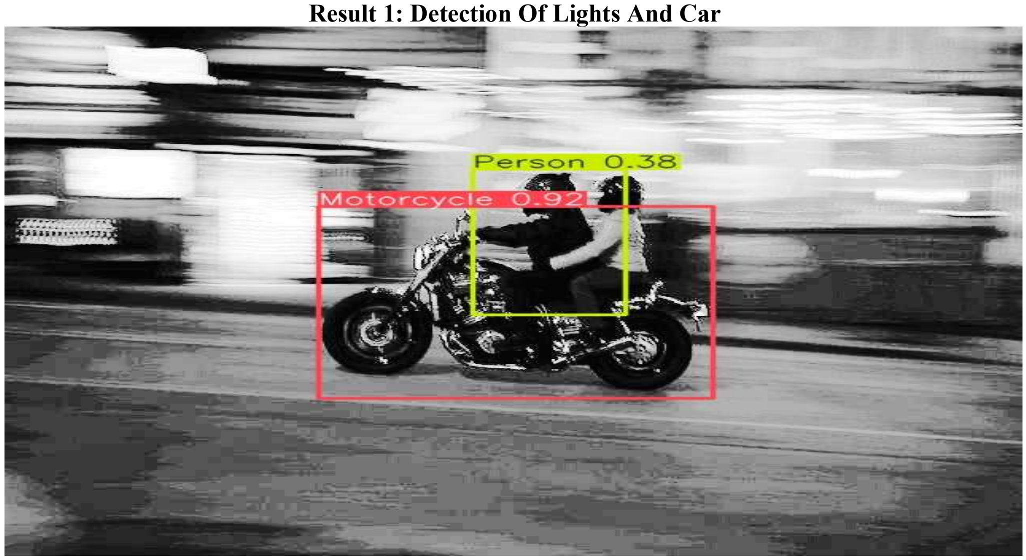
performance may still vary under extreme conditions such as heavy fog or very low illumination. Overall, the proposed approach proves to be robust, efficient, and suitable for intelligent transportation systems and future autonomous driving applications.

Results



Result 1: Detection Of Lights And Car



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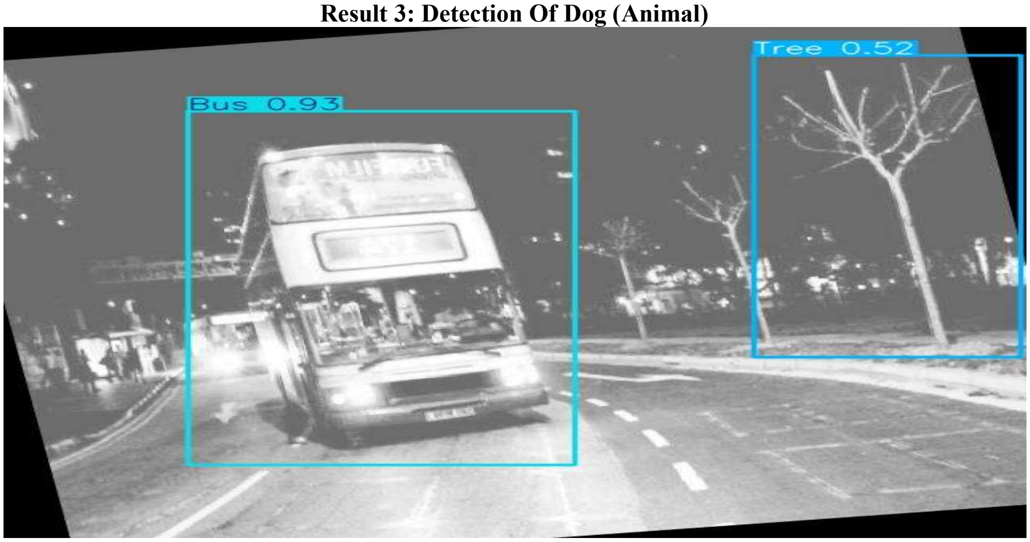
Result 2: Detection Of Motorcycle And Person

Result 3: Detection Of Dog (Animal)



Result 4: Detection Of Bus And Tree

Result 5: Detection Of Car

Conclusion

This project presents an enhanced vehicle detection framework based on the YOLOv10 architecture to address the challenges of detecting vehicles in low-light and nighttime on-board environments. By integrating effective image preprocessing techniques such as adaptive histogram equalization, contrast enhancement, and noise reduction, the system

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significantly improves image quality and enables robust feature extraction under poor illumination conditions. The YOLOv10 model, fine-tuned on diverse low-light datasets, demonstrates strong capability in detecting small, distant, and partially occluded vehicles while minimizing false positives caused by glare and noise.Future Scope

The proposed YOLOv10-based vehicle detection system can be further enhanced in several ways to improve performance and expand its applicability. Advanced deep learning–based image enhancement techniques, such as GAN-based low-light enhancement, can be integrated to handle extremely dark environments more effectively. The system can be extended to support multi-object tracking, enabling continuous monitoring of vehicles across video frames for better traffic analysis.

In addition, sensor fusion techniques combining camera data with LiDAR, radar, or infrared sensors can be incorporated to improve detection accuracy under adverse weather conditions such as fog, rain, or heavy glare. Model optimization methods like pruning, quantization, and edge-AI acceleration can be applied to reduce computational complexity and power consumption, making the system more suitable for real-time embedded applications.

Furthermore, the framework can be expanded to include vehicle classification, behavior prediction, and collision avoidance systems, contributing to more advanced autonomous driving and intelligent transportation solutions. Overall, the future scope focuses on improving robustness, scalability, and real-world deployment capabilities of the system.

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