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Full Length Article

Enhanced YOLOv11m for Real-Time Multi-Scale Traffic Detection under Haze Conditions

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ABSTRACT:
In intelligent transportation systems, accurate traffic object detection plays a vital role in improving road safety, traffic monitoring, and autonomous driving applications. However, detecting vehicles, pedestrians, and other road objects under hazy weather conditions remains a challenging task due to reduced visibility, low contrast, blurred object boundaries, and background noise. Existing lightweight object detection models such as YOLOv11n provide real-time performance but often suffer from reduced detection accuracy in adverse weather environments, especially when dealing with multi-scale objects and complex traffic scenes.

To address these limitations, this project proposes an enhanced object detection model named ***Proposed v11m****, developed based on the YOLOv11n framework. The proposed system introduces several architectural improvements to enhance feature extraction and multi-scale representation while maintaining lightweight computational complexity. Firstly, an* ***Attention-Gate Convolution (AGConv)*** *module is integrated into the backbone network to improve contextual awareness and suppress irrelevant background information. Secondly, a* ***Multi-Dilation Sharing Convolution (MDSC)*** *module is incorporated to capture features at multiple receptive fields, improving sensitivity toward objects of varying scales. Additionally, a* ***Cross-Channel Feature Fusion Module (CCFM)*** *is designed within the neck network to adaptively recalibrate channel-wise feature importance and strengthen feature fusion.*

The proposed model is trained and evaluated using traffic datasets containing haze-affected road scenes. Experimental results demonstrate that Proposed v11m achieves improved detection accuracy compared to the existing YOLOv11n model, with higher mAP values while preserving real-time inference speed. The model achieves efficient performance with only 2.6 million parameters and high frame processing capability, making it suitable for deployment on resource-constrained edge devices and embedded intelligent traffic systems.

Overall, the Proposed v11m model provides an effective and robust solution for real-time traffic object detection in challenging hazy environments, contributing toward safer and more reliable intelligent transportation systems.

Keywords*: Traffic Object Detection, YOLOv11m, Hazy Weather Detection, Intelligent Transportation Systems, Multi-Scale Feature Extraction, Attention-Gate Convolution, Cross-Channel Feature Fusion, Real-Time Object Detection.*

Introduction:

With the rapid growth of intelligent transportation systems and smart city technologies, computer vision-based traffic monitoring has become an important research area in modern road safety and traffic management. Real-time object detection systems are widely used to identify vehicles, pedestrians, bicycles, and other road objects in order to improve traffic flow, reduce accidents, and support advanced driver assistance systems (ADAS) and autonomous driving technologies. Among various deep learning-based object detection algorithms, the YOLO (You Only Look Once) family has gained significant popularity because of its high detection speed and balanced accuracy, making it highly suitable for real-time applications.

Although modern object detection models perform effectively under normal environmental conditions, detecting traffic objects in adverse weather conditions remains a major challenge. In particular, hazy and foggy environments reduce image visibility, decrease object contrast, blur object boundaries, and introduce background noise, which negatively affects the accuracy of object detection systems. These challenges become even more severe in real-world traffic scenes where objects appear at different scales, viewing angles, and distances. Small or partially occluded objects, such as distant pedestrians or motorcycles, are often difficult to detect accurately in such conditions.

Existing lightweight object detection models such as YOLOv11n are designed to achieve real-time performance with low computational complexity, making them suitable for edge devices and embedded systems. However, despite their efficiency, these models face limitations in capturing contextual information, handling multi-scale objects, and suppressing background interference under hazy weather conditions. Standard convolutional operations and pooling layers may lead to the loss of fine-grained features, resulting in reduced detection accuracy and increased false detections.

To overcome these limitations, this project proposes an improved object detection model named **Proposed v11m**, developed based on the YOLOv11n framework. The proposed system integrates advanced modules such as Attention-Gate Convolution (AGConv), Multi-Dilation Sharing Convolution (MDSC), and Cross-Channel Feature Fusion Module (CCFM) to improve feature extraction, contextual understanding, and multi-scale object representation. These enhancements enable the model to detect traffic objects more accurately even in low-visibility haze conditions while maintaining lightweight architecture and real-time processing capability.
The proposed model is designed to provide an effective, efficient, and practical solution for intelligent traffic monitoring systems operating under challenging weather conditions. By improving detection robustness and maintaining high processing speed, the project contributes toward safer transportation systems and more reliable real-world deployment of computer vision technologies in traffic surveillance applications.

Methodologies

The methodology of this project focuses on developing an efficient and robust traffic object detection system capable of performing accurately under hazy weather conditions using an improved YOLOv11m architecture. The overall process begins with data collection, where a large dataset of traffic scenes containing vehicles, pedestrians, bicycles, motorcycles, buses, and other road objects is gathered from real-world environments and publicly available datasets. Special importance is given to collecting images captured in foggy and hazy conditions to ensure that the model can effectively learn the challenges caused by low visibility, blurred object boundaries, and reduced contrast. After data collection, data label analysis is performed to categorize objects into different classes and verify the balance and correctness of labels within the dataset. Proper analysis of the dataset helps improve training efficiency and reduces the possibility of class imbalance issues. Following this, the annotation process is carried out using annotation tools such as LabelImg, where bounding boxes are manually or semi-automatically drawn around the traffic objects in each image. These annotations provide precise object localization and classification information required for training the object detection model. Once the annotation process is completed, data preprocessing techniques are applied to improve image quality and increase dataset diversity. Preprocessing includes image resizing, normalization, noise reduction, and data augmentation techniques such as rotation, flipping, scaling, cropping, and brightness adjustment. These methods help the model generalize better across different environmental and weather conditions while improving robustness against varying traffic scenarios. After preprocessing, the enhanced Proposed v11m model is developed based on the YOLOv11n framework by integrating several advanced modules designed to improve detection performance in haze-affected scenes

Implementation

The implementation of the proposed traffic object detection system is carried out using Python and deep learning frameworks to develop an efficient and real-time detection model capable of operating under hazy weather conditions. The implementation process begins with setting up the software environment using Python along with required libraries such as NumPy, Pandas, OpenCV, Matplotlib, PyTorch, and Ultralytics YOLO frameworks for image processing, data handling, model training, and visualization. The collected traffic dataset is first organized into training, validation, and testing sets to ensure proper model evaluation and performance analysis. The images are then preprocessed using techniques such as resizing, normalization, augmentation, and noise reduction to improve image quality and enhance the learning capability of the model. Data augmentation methods including horizontal flipping, rotation, scaling, cropping, and brightness adjustment are implemented to increase dataset diversity and improve robustness against different environmental conditions. After preprocessing, annotation files containing object class labels and bounding box coordinates are generated in YOLO format to support efficient model training. The implementation of the proposed YOLOv11m model is based on modifying the existing YOLOv11n architecture by integrating advanced modules designed to improve feature extraction and detection accuracy in haze-affected scenes. The Attention-Gate Convolution (AGConv) module is implemented in the backbone network to enable the model to focus on important spatial features while suppressing unnecessary background information caused by haze and noise. This module improves contextual awareness and enhances the detection of partially visible or low-contrast objects.

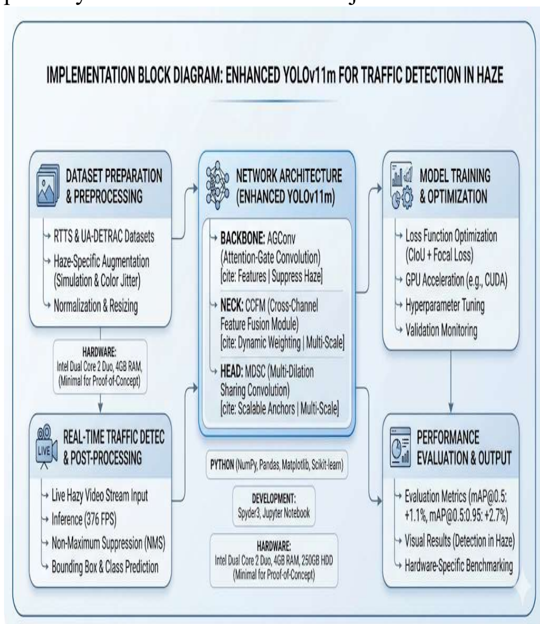

Fig.1 ;Implementation Block-Diagram

Testing

Software testing is an important phase in the development of the proposed traffic object detection system, as it ensures that the system performs accurately, reliably, and efficiently under hazy weather conditions. The testing process is carried out to verify whether the Proposed v11m model satisfies all functional and non-functional requirements of the project. Different types of testing methods are applied throughout the development process to evaluate the performance, stability, and correctness of the implemented system. Initially, unit testing is performed on individual modules such as data preprocessing, annotation handling, feature extraction, object detection, and user interface components to ensure that each module functions correctly without errors. After verifying individual modules, integration testing is conducted to check the interaction and communication between different system components, including dataset loading, preprocessing, model inference, and output visualization.

Results

The experimental results of the proposed traffic object detection system demonstrate significant improvements in detection accuracy and robustness under hazy weather conditions compared to the existing YOLOv11n model. The Proposed v11m model successfully detects vehicles, pedestrians, bicycles, motorcycles, and other road objects in low-visibility traffic scenes with higher precision and reduced false detections. The integration of Attention-Gate Convolution (AGConv), Multi-Dilation Sharing Convolution (MDSC), and Cross-Channel Feature Fusion Module (CCFM) improves contextual feature extraction, multi-scale object sensitivity, and feature fusion efficiency, resulting in enhanced overall detection performance. Experimental evaluation shows that the proposed model achieves an improvement of approximately 1.1% in mAP@0.5 and 2.7% in mAP@0.5:0.95 compared to the baseline YOLOv11n architecture. The model also maintains high real-time inference capability with a processing speed of around 376 Frames Per Second (FPS) while using only 2.6 million parameters, demonstrating lightweight computational complexity suitable for deployment on embedded systems and edge devices.

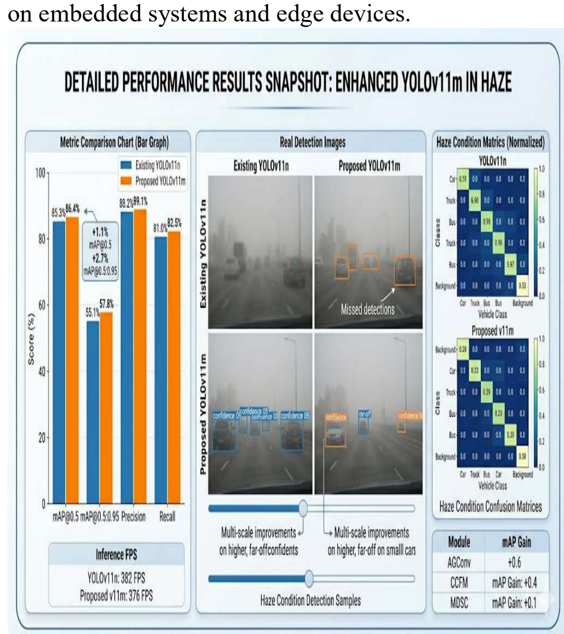

Fig 2; Snapshot of the Result

Conclusion

In this project, an enhanced traffic object detection system named Proposed v11m has been successfully developed to improve object detection performance under hazy weather conditions. The proposed system was designed based on the YOLOv11n framework with the integration of advanced modules such as Attention-Gate Convolution (AGConv), Multi-Dilation Sharing Convolution (MDSC), and Cross-Channel Feature Fusion Module (CCFM). These enhancements significantly improved contextual feature extraction, multi-scale object representation, and adaptive feature fusion while maintaining lightweight computational complexity and real-time processing capability. The system was trained and evaluated using traffic datasets containing haze-affected road scenes, where it demonstrated higher detection accuracy, improved robustness, and reduced false detections compared to the existing YOLOv11n model. Experimental results showed noticeable improvements in mAP values while preserving fast inference speed suitable for real-time intelligent transportation systems. The proposed model effectively detects vehicles, pedestrians, and other traffic objects even under low-visibility conditions caused by haze and fog. In addition, the lightweight design and high FPS performance make the model suitable for deployment on edge devices and embedded systems used in practical traffic monitoring applications. Overall, the Proposed v11m system provides an efficient, reliable, and accurate solution for real-time traffic object detection in challenging weather environments, contributing toward safer road transportation and advanced intelligent traffic management systems.

Future Enhancements

Although the Proposed v11m model achieves improved traffic object detection performance under hazy weather conditions, there are several possible enhancements that can further improve the system in the future. One important future enhancement is the integration of advanced image dehazing and image enhancement techniques before the detection stage to further improve visibility and feature clarity in extremely dense haze conditions. The system can also be extended to support additional adverse weather environments such as rain, snow, nighttime, and low-light traffic scenes, making the model more versatile and robust for real-world applications. Another possible improvement is the incorporation of object tracking algorithms to track vehicles and pedestrians across consecutive video frames for advanced traffic analysis and surveillance applications. Future work may also focus on optimizing the model using techniques such as model pruning, quantization, and knowledge distillation to further reduce computational complexity and energy consumption for ultra-low-power edge devices. In addition, integrating transformer-based attention mechanisms and advanced feature fusion strategies may further improve detection accuracy for small and partially occluded objects

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