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Section:2

Paper Title:

PRE-YOLO: A Lightweight Model for Detecting Helmet-Wearing of Electric Vehicle Riders on Complex Traffic Roads

Paper Link:

https://www.mdpi.com/2076-3417/14/17/7703

1 Summary

1.1Motivation

The widespread use of electric vehicles has led to an increase in traffic-related injuries and fatalities, with head injuries being a primary cause of death. Despite the availability of helmets as protective gear, their usage remains inconsistent due to factors such as inconvenience or lack of awareness. Traditional detection methods fail to account for real-world complexities, including small helmet sizes, diverse helmet styles, and varying traffic conditions. The study aims to address these gaps by developing an efficient, accurate, and lightweight model capable of detecting helmet-wearing behavior in complex environments.

1.2 Contribution

This paper introduces PRE-YOLO, a modified YOLOv8n framework designed to improve helmet-wearing detection in resource-constrained environments. The key innovations include:

1. Refining the detection architecture to enhance small-object recognition.
2. Implementing the RFCAConv module to capture both spatial and channel-level features effectively.

3. Incorporating an EMA-based C2f module to strengthen feature extraction without increasing computational overhead.

The results demonstrate enhanced precision, recall, and detection accuracy, offering a practical solution for traffic safety monitoring.

1.3 Methodology

Small Object Detection Layer:

- A new detection layer is introduced to focus on small targets like helmets by performing 4× downsampling on input images.
- This improves the extraction of shallow feature information for better accuracy in detecting small objects.
- The large object detection layer is pruned to reduce model parameters and size.

Receptive-Field Coordinate Attention Convolution (RFCAConv):

- Replaces standard convolution to improve spatial and channel feature extraction with reduced computational cost.

Exponential Moving Average (EMA)-Enhanced C2f Module:

- The EMA module is integrated into the C2f module to improve feature perception and strengthen attention distribution without increasing computational overhead. This ensures better feature continuity and captures critical details for accurate detection.

Lightweight Model Optimization:

- The architecture is streamlined by reducing unnecessary layers and focusing on key modules, leading to a 33% reduction in model parameters and a smaller model size.

Training and Dataset Preparation:

- A dataset of 3827 traffic images was augmented with flipping, brightness adjustment, and noise addition to improve generalization.

1.4 Conclusion

The model demonstrated improved detection accuracy (up to 95.7% mAP@0.5) while reducing model size and computational complexity by 33%. This makes it suitable for real-world deployment in resource-constrained environments.

2 Limitations

2.1 First Limitation

The model's performance in extreme conditions, such as poor lighting, heavy occlusion, or dynamic scenes, remains constrained. The reliance on specific datasets for training also limits generalizability to more diverse conditions.

2.2 Second Limitation

The PRE-YOLO model struggles with high-speed scenarios, where rapid vehicle movement can lead to missed detections. Although the model achieves sufficient frame rates for current detection tasks, the reduction in FPS due to additional computational layers might hinder scalability for high-performance, real-time systems.

3 Synthesis

The innovations in PRE-YOLO extend the capabilities of real-time object detection in traffic monitoring systems, offering a scalable and efficient solution for helmet-wearing enforcement. Its lightweight architecture makes it well-suited for deployment on edge devices like roadside cameras or drones, where computational resources are limited. The research lays the groundwork for further developments in intelligent transportation systems, particularly in integrating detection models with broader safety applications, such as seatbelt usage or pedestrian safety.

Future work could focus on addressing the limitations by enhancing the model's robustness under extreme conditions, such as heavy rain or fog, and by optimizing its real-time capabilities for faster-moving targets. Expanding the training dataset to include more diverse scenarios could also improve generalizability, paving the way for applications in global traffic safety initiatives.