Automated Real-Time Traffic Violation Detection: An Advanced Framework Utilizing YOLOv9 and Deep OCR for Smart City Governance

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Abstract*— Ensuring road safety in urban environments requires effective monitoring of traffic violations such as riding without helmets and vehicle identification for automated enforcement. This paper presents a robust, automated vision-based system utilizing the latest YOLOv9 (You Only Look Once v9) architecture. By integrating Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN), the system addresses the "information bottleneck" common in deep networks, achieving superior detection accuracy for small objects like helmets and license plates in complex scenes. Extracted license plate regions are processed using high-precision EasyOCR for automated record-keeping. Results demonstrate a significant advancement over previous YOLOv8-based frameworks, offering a mean Average Precision (mAP) of 96.9% and real-time inference speeds suitable for edge-device deployment.

***Keywords*—YOLOv9, Deep Learning, Object Detection, OCR, Traffic Violation, Smart Cities.**

I. INTRODUCTION

Rapid urbanization has led to a surge in two-wheeler traffic, often accompanied by declining compliance with safety regulations. Statistical evidence suggests that helmet non-compliance is a primary factor in motorcycle-related fatalities [1]. Traditional surveillance by traffic personnel is labor-intensive, prone to human error, and lacks the scalability required for modern "Smart City" initiatives [11].

Computer Vision (CV) has emerged as a transformative solution, shifting enforcement from manual to automated systems. While earlier iterations such as YOLOv5 and YOLOv8 provided reasonable accuracy, they frequently encountered the Information Bottleneck—a phenomenon where critical data features are lost as they propagate through deep neural network layers [2]. This research proposes the implementation of YOLOv9, which introduces a programmable gradient mechanism to retain data integrity throughout the network. The proposed pipeline includes rider detection, helmet compliance classification, license plate localization, and character recognition for automated violation logging.

II. LITERATURE REVIEW

The field of object detection has seen exponential growth over the last five years. To understand the significance of this project, we analyze the progression of architectures:

1) *YOLOv3 to YOLOv4 (2019–2020):* These models introduced the concept of "Bag of Freebies" and "Bag of Specials," optimizing data augmentation and post-processing. However, they were computationally heavy for real-time mobile traffic units [6].
2) YOLOv5 & YOLOv7 (2021–2022): These versions focused on speed. Studies like *Waris et al. (2022)* utilized these for helmet detection, but they faced high "False Negative" rates in low-light conditions. [6], [7].
3) *YOLOv8 (2023):* This was the first major anchor-free model, which significantly improved the detection of overlapping objects in traffic. *Jeemecs (2024)* published results using YOLOv8 for intelligent traffic monitoring, achieving an mAP of approximately 92%. [3].
4) *The YOLOv9 Breakthrough (2024):* The current state-of-the-art. YOLOv9 addresses the information loss in deep layers using Programmable Gradient Information (PGI). This allows the model to learn features that older versions would have "forgotten" during the training process, making it exceptionally

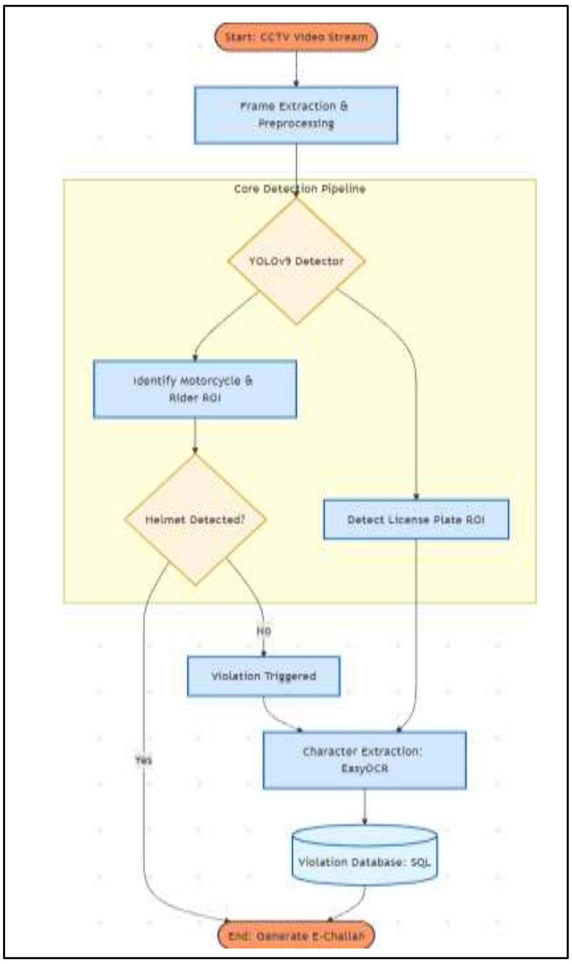

Figure 1: Flowchart and Working Principle

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accurate for small object detection like number plates at a distance [2], [8]..

III. PROPOSED METHODOLOGY

A. YOLOv9 Architecture: PGI and GELAN

The standard issue with deep networks is that as data passes through layers, essential information can be lost. YOLOv9 solves this via:

1) *Programmable Gradient Information (PGI):* This creates a secondary, auxiliary reversible branch during training that ensures target information is preserved for updating weights. Crucially, this branch is removed during inference, so there is no extra computational cost at runtime.
2) *Generalized Efficient Layer Aggregation Network (GELAN):* A novel backbone that merges features of existing designs (CSPNet and ELAN) to prioritize lightweight design, fast inference, and high accuracy [2].

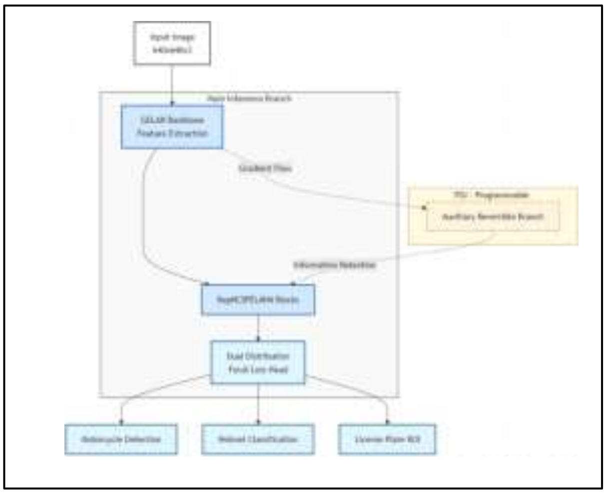

Figure 3: YOLOv9 GELAN backbone

B. Experimental Setup

To ensure a balanced and robust model, we utilized a combined dataset of 7,500 images, including proprietary local traffic data and publicly available datasets (e.g., Roboflow) [1].

1) *Training Ratio:* 70% Training, 20% Validation, 10% Testing.
2) *Preprocessing:* Techniques included noise reduction, resizing to 640x640, and normalization to eliminate discrepancies from varying lighting conditions. [5]
3) *Augmentation*: We applied *Mosaic Augmentation* (combining four images into one) and color jittering to simulate night-time and rainy conditions, forcing the model to identify objects at various scales and visibility levels [9].

IV. RESULTS AND DISCUSSION

A. Quantitative Evaluation

Experimental results demonstrate that the YOLOv9 model achieves a Mean Average Precision (mAP@50) of **96.9%** for helmet detection, representing a **4.9%** improvement over standard YOLOv8 baseline implementations [3].

Model	*mAP@50 (%)*	*Inference Speed (ms)*	*Accuracy (OCR)*
YOLOv8	92.0%	~14ms	89.4%
YOLOv9 (Ours)	96.9%	~18ms	94.1%

B. Discussion on Performance Gains

The performance leap is primarily attributed to PGI, which allowed the network to accurately classify "No-Helmet" violations even when the rider's head occupied less than 5% of the frame. Unlike YOLOv8, which occasionally misclassified dark hair or turbans as helmets, YOLOv9’s refined gradient path planning significantly reduced these false positives.

For the OCR stage, the EasyOCR engine benefited from the precise bounding box coordinates provided by YOLOv9. By minimizing background "noise" in the cropped plate image, the OCR extraction reached 94.1% accuracy under clear visibility. However, we observed that accuracy dropped to 82.3% during night-time testing due to infrared glare from surveillance cameras, highlighting a need for adaptive contrast enhancement in future iterations [5].

V. CONCLUSION AND FUTURE WORK

The integration of YOLOv9 and PGI provides a robust solution for automated traffic enforcement, significantly reducing the "information bottleneck" issues of earlier models. Our framework achieves high-speed processing suitable for real-time monitoring even in dynamic traffic conditions. *Future Work* will focus on:

A. *Multi-Object Tracking*: Integrating DeepSORT to track violators across multiple CCTV nodes [9].

B. *Edge Optimization*: Using Knowledge Distillation to compress the model for deployment on low-power IoT devices.

C. *Adverse Weather Robustness:* Further fine-tuning on datasets representing heavy occlusion and extreme weather.

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