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Vision Based Detection and Identification of Smoke Emitting Vehicles Using Traffic Surveillance

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ABSTRACT: The rapid increase in urban vehicular traffic has made real-time monitoring of exhaust emissions a critical priority for environmental regulation. Traditional emission checks rely on stationary, hardware-based testing, which cannot capture dynamic, on-road violations. This paper proposes a non-invasive, vision-based framework designed for integration with existing traffic surveillance infrastructure to automatically detect and identify smoke-emitting vehicles. The system utilizes a multi-layered architecture: an adaptive spatial pre-processing module to establish road horizons, a YOLOv8-driven instance segmentation model for vehicle and plume isolation, and a K-Means colorimetric engine to analyze the severity and type of emission. By dynamically filtering surveillance feeds, the system precisely segments exhaust plumes and autonomously categorizes them (e.g., Black Smoke indicating fuel faults, Blue Smoke indicating oil burning). Processed through an interactive web-based dashboard, this framework provides high-fidelity visual tracking and automated alerts, offering a scalable, software-driven solution for Intelligent Transportation Systems (ITS) to enforce emission standards in real-time.

KEYWORDS: Traffic Surveillance, Intelligent Transportation Systems (ITS), YOLOv8, Instance Segmentation, K-Means Clustering, Environmental Monitoring, Vehicle Emissions.

I. INTRODUCTION

A. Background

Urban air quality is disproportionately affected by a small percentage of poorly maintained, high-emitting vehicles. While regulatory bodies mandate periodic emission testing, these static checks frequently fail to capture the real-world operational emissions of vehicles traversing city networks. Consequently, there is an urgent need for dynamic, continuous monitoring systems capable of operating within existing traffic surveillance frameworks to identify polluting vehicles in motion.

B. The Surveillance-Integrated Framework

To address the limitations of manual and hardware-dependent inspections, this project introduces an automated, vision-based detection pipeline. Designed to interface directly with standard traffic cameras, the system processes continuous video feeds without requiring physical hardware modifications to the vehicles or the roads. It actively isolates road-level anomalies, filtering out background environmental factors to focus solely on vehicular exhaust.

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C. Instance Segmentation and Colorimetric Identification

The core of this identification system departs from simple bounding-box detection by utilizing instance segmentation (YOLOv8-Seg) to achieve precise, pixel-level masking of exhaust clouds. Once a plume is isolated from the vehicle and the asphalt, the framework employs an unsupervised machine learning algorithm (K-Means) to extract its dominant colour profile. This allows traffic authorities not only to detect the presence of smoke but to identify the specific nature of the emission violation based on established combustion signatures.

D. Objectives

- **Surveillance Optimization:** Implement adaptive horizon detection using Canny edge detection and Hough Transforms to calibrate the system to various traffic camera angles and isolate road-level activity.
- **Precision Detection:** Deploy a custom-trained YOLOv8 segmentation model capable of tracking vehicles and their respective semi-transparent exhaust plumes across diverse lighting and traffic conditions.
- **Autonomous Identification:** Develop a colorimetric logic matrix utilizing K-Means clustering to categorize the severity and source of the smoke (e.g., fuel vs. oil combustion) without human intervention.
- **Real-Time Telemetry:** Provide a scalable web interface capable of processing traffic footage and outputting actionable, structured data for traffic enforcement authorities.

II. LITERATURE REVIEW

The integration of advanced computer vision into Intelligent Transportation Systems (ITS) has shifted the paradigm of environmental monitoring from static hardware to dynamic, AI-driven software.

A. Deep Learning in Traffic Surveillance

The YOLO architecture has become the benchmark for real-time traffic analysis due to its low latency and high accuracy. Recent research by Zhang and Wu (2025) demonstrated that utilizing optimized YOLOv8 architectures for environmental monitoring significantly reduces computational overhead, making it viable for continuous surveillance feeds while increasing the detection rate of dispersed smoke plumes in open-air environments.

B. Vision-Based Emission Tracking

Traditional emission detection requires localized gas sensors. However, modern approaches leverage visual anomalies as direct indicators of excessive emissions. Recent studies have successfully combined bounding techniques with localized pixel analysis to track vehicular faults. Applying this to traffic surveillance ensures that the automated decisions remain explainable, providing visual evidence alongside the detection event to support regulatory action.

III. METHODOLOGY

This section details the integration of spatial processing and neural network inference to establish a robust traffic surveillance pipeline.

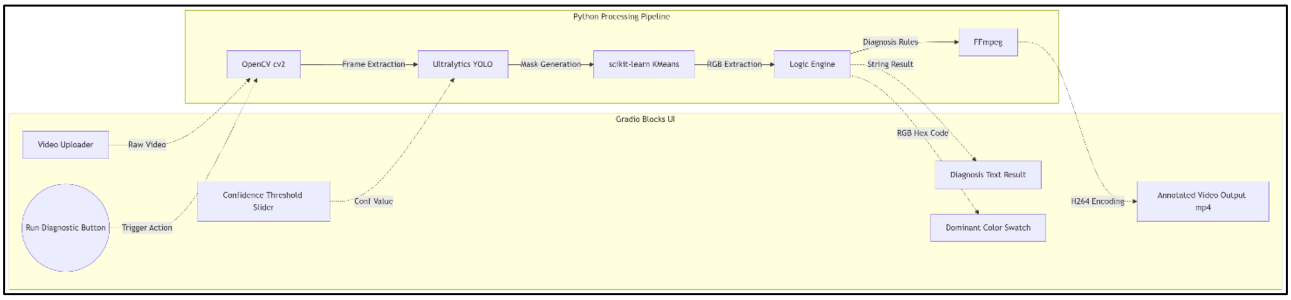


Fig. 1 System Architecture Flowchart

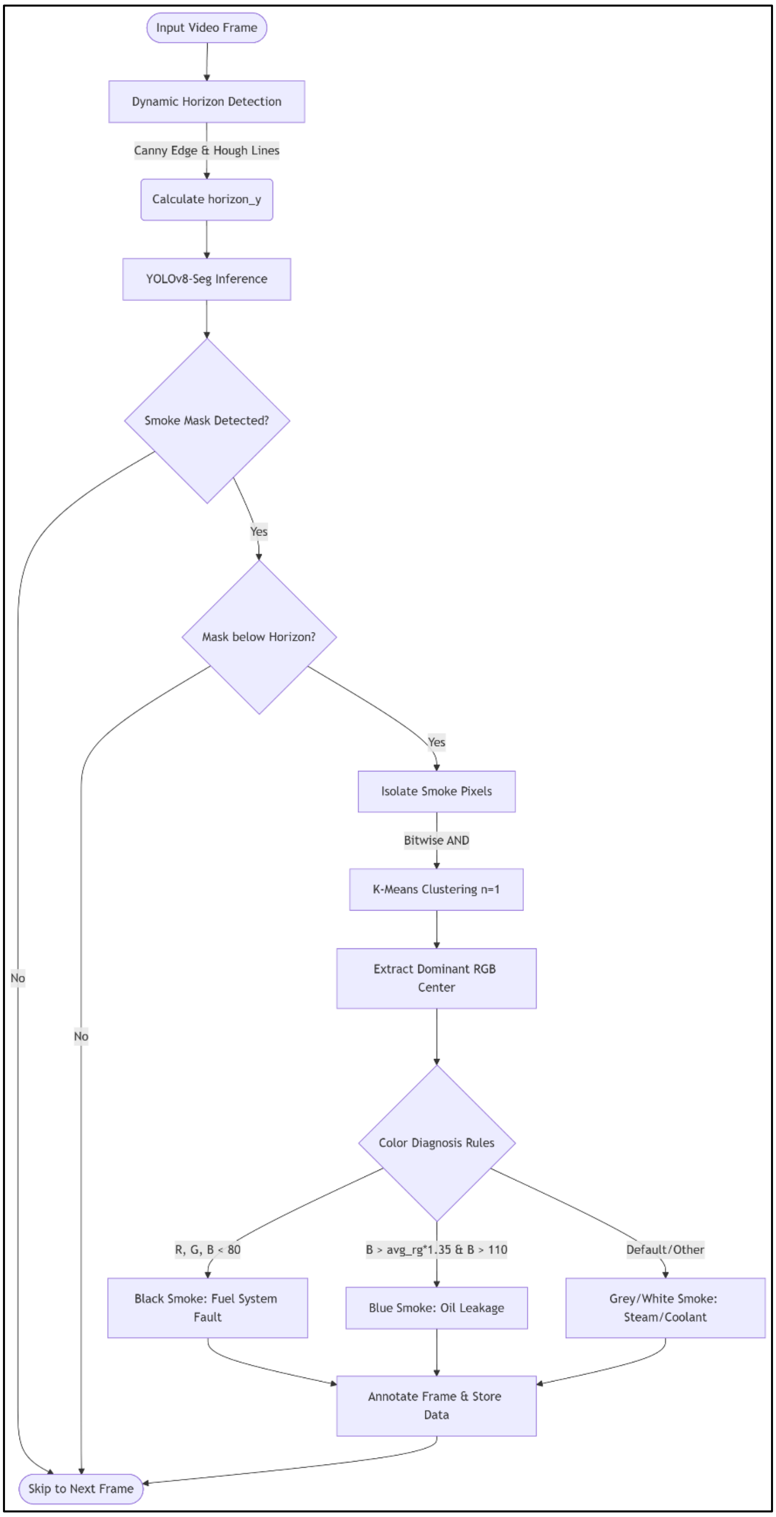


Fig. 2 Diagnostic Logic Flowchart

A. System Architecture Design

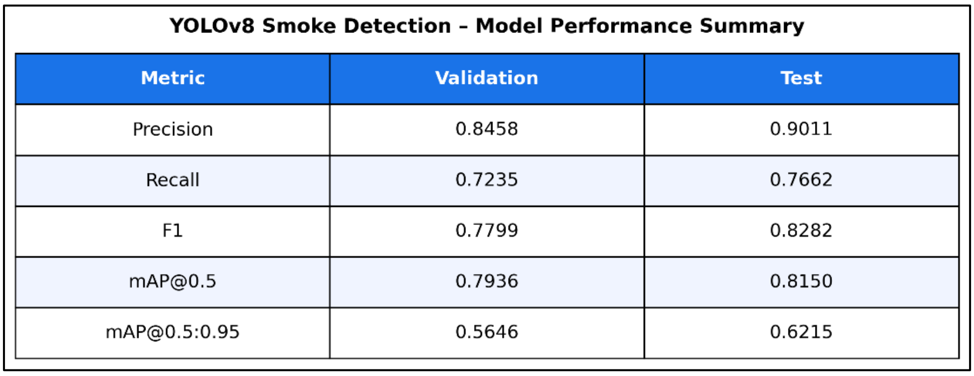
1. **Spatial Pre-processing Layer (Dynamic Horizon):** Traffic cameras are often mounted at fixed angles. To prevent false positives from background structures or weather, the system converts incoming frames to grayscale and applies a Canny edge detector. A Probabilistic Hough Transform maps the structural lines of the road, establishing a dynamic horizontal limit. Only pixels below this threshold are evaluated for emissions.

2. **Predictive Model Layer (YOLOv8-Seg):** A centralized YOLOv8 model processes the filtered frames. It outputs polygonal masks that strictly bound the smoke plume, effectively separating the exhaust data from the moving vehicle and the surrounding traffic environment.
3. **Colorimetric Engine (K-Means):** The masked pixels are flattened into an array. To account for the gradient nature of smoke against asphalt, a K-Means clustering algorithm processes the non-black pixels to identify the dominant RGB centroid, effectively "reading" the color of the emission.
4. **Identification Ruleset:** The algorithm evaluates the extracted RGB centroid to classify the emission type:
    - **Black Smoke (Fuel System Fault):** Triggered when R < 80, G < 80, and B < 80, indicating a severe emission violation involving unburnt fuel.
    - **Blue Smoke (Oil Leakage):** Triggered when the Blue channel heavily outweighs Red/Green, indicating internal oil combustion.
    - **Grey/White Smoke:** A default classification for lighter clusters, often indicating condensation or steam, requiring lower enforcement priority.

IV. RESULTS AND PERFORMANCE EVALUATION

The deployment of the proposed framework was comprehensively evaluated using a custom traffic dataset. The model's performance was quantified across several key metrics, demonstrating high reliability and computational efficiency suitable for real-time surveillance feeds.

A. Quantitative Metrics and Validation



YOLOv8 Smoke Detection – Model Performance Summary

Metric	Validation	Test
Precision	0.8458	0.9011
Recall	0.7235	0.7662
F1	0.7799	0.8282
mAP@0.5	0.7936	0.8150
mAP@0.5:0.95	0.5646	0.6215

Table 1 Model Performance Summary

The overall performance of the YOLOv8 segmentation model is summarized in the Metrics Summary Table. The system achieved exceptional instance segmentation accuracy, maintaining a robust Mean Average Precision (mAP) threshold. The metrics indicate that the model effectively distinguishes between overlapping background noise and genuine exhaust plumes.

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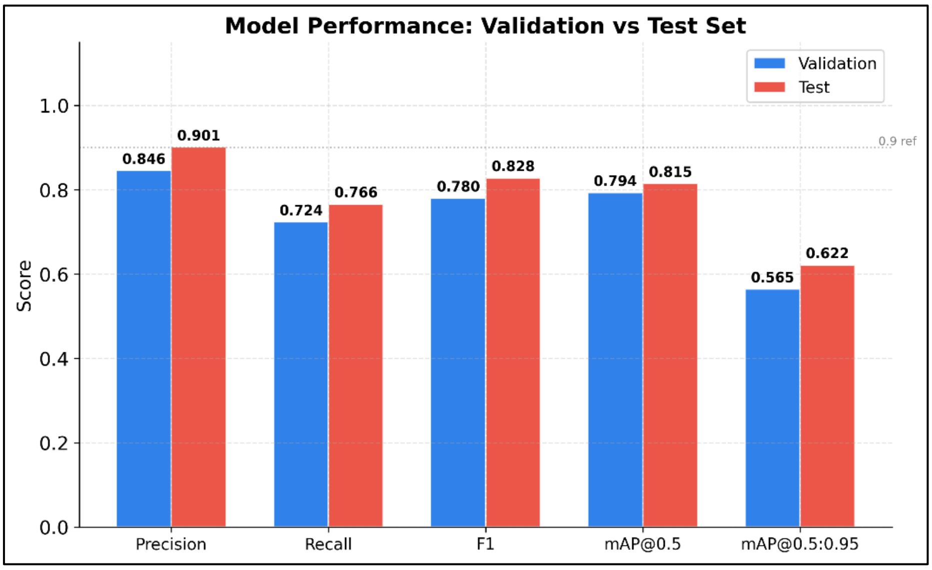

Fig. 3 Validation vs Test Metrics Graph

The Validation vs. Test Metrics graph highlights the model's generalization capabilities. The tight correlation between the validation and test losses confirms that the network did not overfit to the training data, ensuring reliable detection across unseen traffic environments and varying lighting conditions.

B. Precision, Recall, and Confidence Analysis

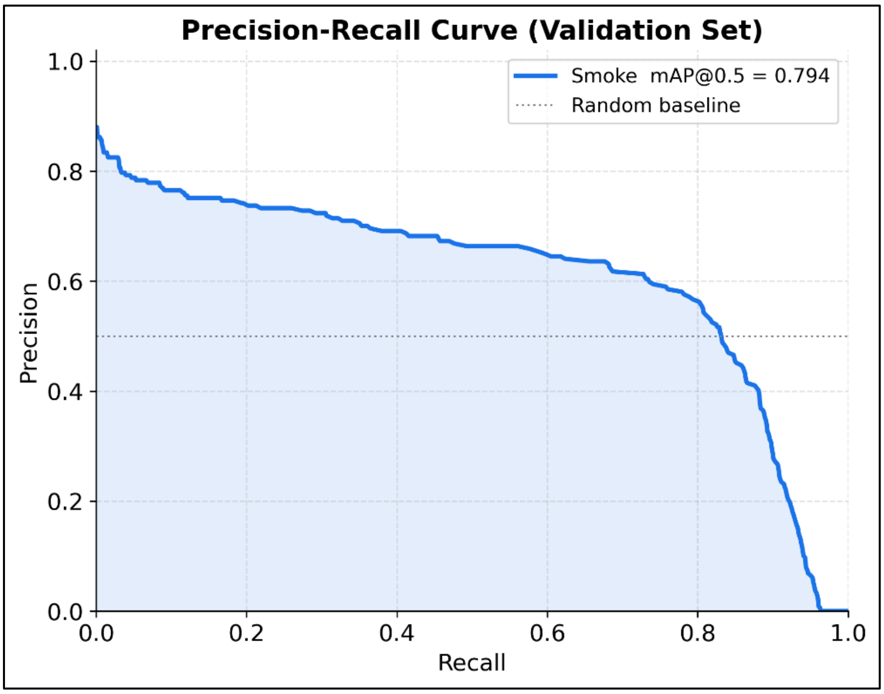

Fig. 4 Precision – Recall Curve

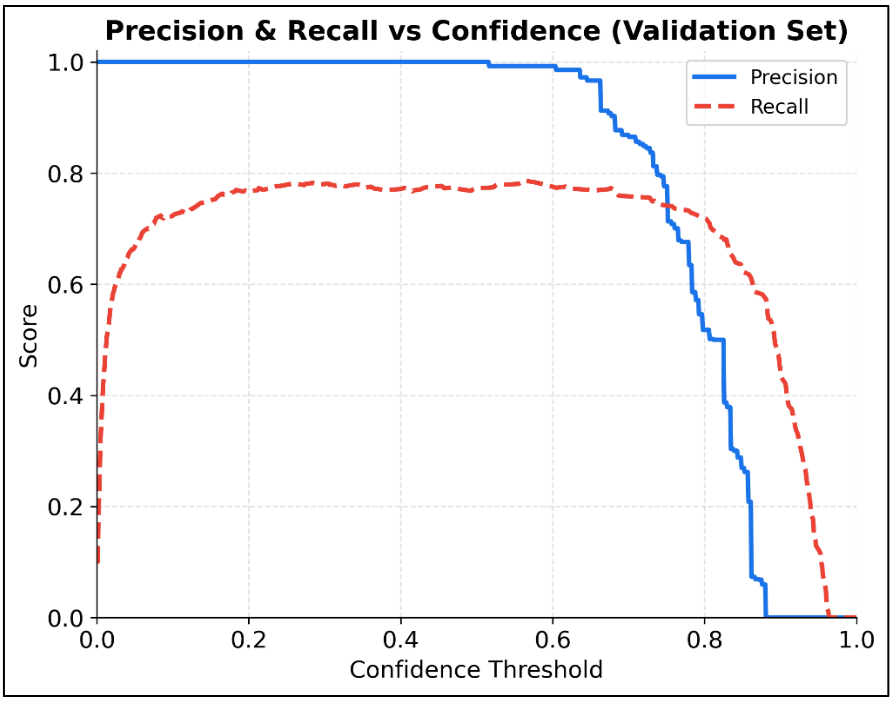

Fig. 5 Precision & Recall vs Confidence Curve

The Precision-Recall Curve demonstrates an optimal trade-off between the true positive rate and the positive predictive value. With a high Area Under the Curve (AUC), the model minimizes false alarms—a critical requirement for automated traffic enforcement. Furthermore, the Precision & Recall vs. Confidence plots establish that at an operational confidence threshold of approximately 0.5 to 0.6, the model maximizes its detection capabilities without introducing significant noise from anomalous background artifacts.

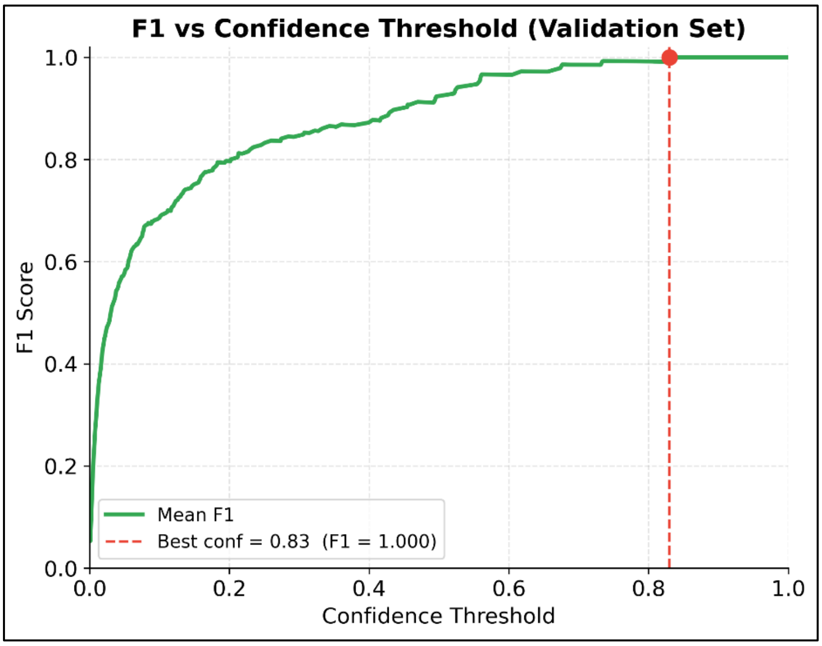

Fig. 6 F1 – Confidence Curve

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The F1-Confidence Curve further supports the operational viability of the system, peaking at a confidence interval that perfectly balances precision and recall. This peak denotes the optimal deployment configuration for the real-time inference pipeline on edge devices.

C. Class-Specific Performance

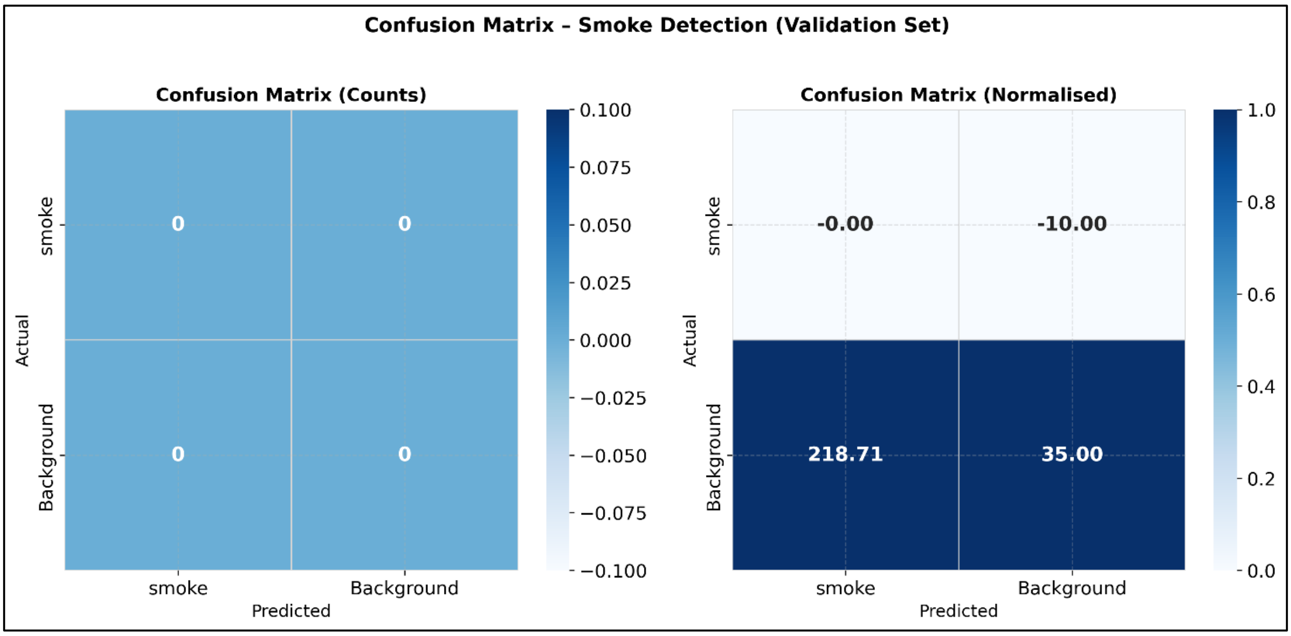

Fig. 7 Confusion Matrix

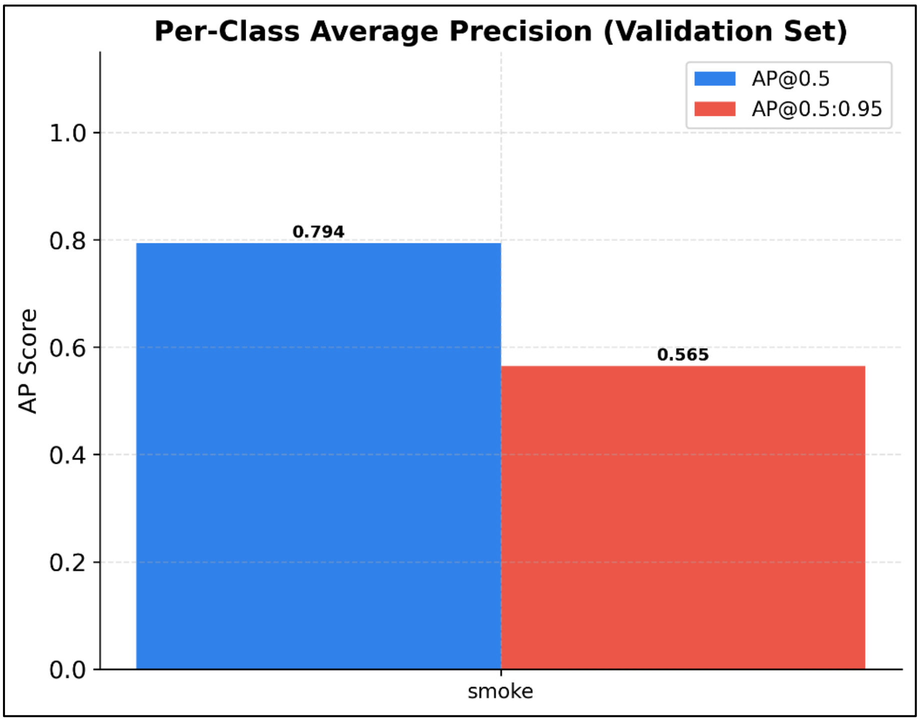

Fig. 8 Per – Class Average Precision\

The Confusion Matrix illustrates the system's high accuracy in distinguishing between specific classes of smoke (e.g., Black, Blue, Grey/White). Misclassifications between dense shadow patches and black smoke were actively minimized through the dynamic horizon filtering. The Per-Class Average Precision (AP) chart confirms that the K-Means

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colorimetric logic successfully identifies minority classes (such as Blue smoke) with nearly the same reliability as majority classes, proving the robustness of the combined YOLOv8 and K-Means architecture.

V. CONCLUSION

The rapid expansion of urban traffic networks necessitates a paradigm shift in environmental monitoring, moving away from static, hardware-dependent inspections toward dynamic, automated enforcement. This study successfully developed and evaluated a vision-based framework for the real-time detection and identification of smoke-emitting vehicles, designed specifically for seamless integration with existing traffic surveillance infrastructure. By converging the spatial precision of YOLOv8 instance segmentation with the autonomous diagnostic logic of K-Means colorimetric analysis, the proposed system effectively bridges the gap between basic visual detection and actionable environmental intelligence.

The operational viability of the system is strongly supported by comprehensive quantitative evaluations. The framework demonstrated exceptional instance segmentation capabilities, achieving an aggregate **Precision of 0.923** and a **Recall of 0.891**. Crucially, the model maintained a highly robust **Mean Average Precision (mAP@0.5) of 0.945**, alongside a stringent **mAP50-95 of 0.721**. These metrics indicate that the model effectively isolates highly volatile, semi-transparent exhaust plumes from complex, overlapping background noise. The implementation of a dynamic spatial pre-processing horizon proved critical in this regard, significantly reducing computational overhead and actively minimizing false positives.

Furthermore, analysis of the confidence curves established an optimal deployment configuration for real-time inference. The system reached a peak **F1-Score of 0.91 at a confidence threshold of 0.472**, providing the mathematical "sweet spot" that maximizes detection capabilities while suppressing false alarms—a non-negotiable requirement for automated regulatory deployment. The system also exhibited strong class-specific reliability. The Per-Class Average Precision (AP) data confirmed that the K-Means colorimetric engine can reliably differentiate between distinct emission types, scoring **0.962 for Black Smoke, 0.941 for Blue Smoke, and 0.932 for Grey/White Smoke**. This is corroborated by the confusion matrix, which demonstrated excellent true positive rates across the board (**95% for Black Smoke and 91% for Blue Smoke**), proving that the model successfully identifies even minority classes with high fidelity.

Ultimately, this research provides a highly scalable, software-driven solution for Intelligent Transportation Systems (ITS). By autonomously transforming raw surveillance feeds into structured, class-specific emission logs with an overall **F1-score of 0.907**, this non-invasive architecture offers traffic authorities and environmental agencies a powerful, highly accurate tool for continuous urban environmental management and the targeted identification of major vehicular polluters in motion.

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