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Automated Detection of high emission Vehicles in Road Traffic Monitoring Systems

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Abstract. Air pollution caused by vehicle emissions is a growing problem in cities, especially where traffic is dense and existing monitoring systems fall short. In this project, we introduce an automated detection method that identifies visibly high emission vehicles from traffic footage using the YOLOv8 object detection model. Instead of testing the air for emissions, we looked for visible smoke coming from vehicles, which can be seen in real time through video. We used the Roboflow Smoke Vehicles Dataset with 1,034 labelled traffic images, combined with locally gathered emissions footage provided by regional authorities. Our model, trained and run on Google Colab's T4 GPU, achieved a mean Average Precision (mAP) of 77.7% with inference times under 1 millisecond (0.99 ms). From the results, we believe this model could be useful in real traffic monitoring systems that cities already use. Hence providing a less expensive and more accessible option than sophisticated sensing platforms like EDAR and CARES.

1 Introduction

As cities grow and the number of vehicles rises, it gets harder to control and monitor air quality. Roadside checks and fixed monitoring stations are some existing solutions that offer insightful information, but they sometimes lack the scope or speed required for enforcement. There is a real need for systems that can monitor large areas quickly and without human help. In this work, we chose YOLOv8 for its fast detection performance, ability to handle urban visual complexity, and suitability for deployment on devices with limited computing power [1]. We chose YOLOv8 because it works faster and gives better results than the older models we tested. The architecture (Figure 1) consists of CSPDarknet53 backbone, PANet for grouping features at several scales, and detection heads capable of identifying cars and, dynamic factors like smoke. Notably, YOLOv8 does not rely on fixed anchor boxes; instead, it gains a more flexible understanding of object boundaries, which helps detect irregular shapes such as smoke clouds [2]. Unlike prior studies focused on chemical readings, this paper centers on using visible emissions as a signal for high emission vehicles. This method is faster because it just needs a camera, and no extra sensors to identify pollution. Our review of recent work revealed three main limitations in current emission detection systems that includes high setup costs for remote sensing units, lack of real-time detection of individual violators; and underuse of visual cues like smoke, which often signal engine trouble [3]. To address these gaps, we propose a new system that uses video footage to detect visible emissions using YOLOv8. This approach is tested with a public dataset and evaluated using standard performance metrics. The major contributions of this paper are a computer vision-

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based method for identifying high emission vehicles through smoke analysis, a real-time processing pipeline built on YOLOv8, achieving sub-millisecond inference speed, an implementation strategy compatible with existing city infrastructure; and deployment considerations for integration into traffic enforcement networks can evolve with changing climate realities and provide more accurate, actionable forecasts.

2 Related Work

2.1 Evolution of Vehicle Emission Monitoring

While the dataset is a valuable resource for weather prediction tasks, it is important to note potential biases and limitations. These include possible class imbalances (e.g., more clear days than rainy ones), missing or incomplete data entries, and the geographic scope being limited to a single region, which may affect the generalizability of the findings. Traditional vehicle emission assessment relied heavily on periodic inspections and stationary measurement equipment. However, urban growth and increasing vehicle populations have exposed the limitations of these approaches, driving innovation toward automated, real-time monitoring solutions.

Recently, developments in remote sensing technology have created new possibilities for emission monitoring. Xie et al. de- veloped an innovative hyperparameter optimization framework for remote sensing systems. It demonstrated improved detection accuracy through automated parameter tuning [4]. Their research showed that machine learning can help improve the usual ways we check for vehicle pollution. The integration of deep learning with urban surveillance infrastructure has shown promising results. Li et al. demonstrated how existing city camera networks could be repurposed for pollution monitoring using convolutional neural networks [5]. The approach successfully identified pollution patterns but did not address individual vehicle detection or real-time enforcement applications.

2.2 Regulatory and Policy Framework

Remote sensings usefulness with emission regulations has been well documented by International Council on Clean Transportation. According to Bernard and German's analysis, collecting emissions data from the road gives better results than lab tests when making rules about pollution [6]. However, instead of focusing on identifying specific vehicles, the focus was more on gathering data on a large scale.

Use of remote sensing over conventional testing approaches was shown by BorkenKleefeld and Dallmann [7]. When it came to identifying high emission vehicles, this was true. Those that might pass routine inspections would sometimes malfunction during regular operation. The research did not address implementation costs or the deployment challenges, but it did support the value in continuous monitoring.

2.3 Technological Approaches and Limitations

Current research focuses more on chemical analysis and pollutant quantification. They pay limited attention to visual detection methods. Ghaffarpasand et al. identified that high emission vehicle subsets contribute disproportionately to total pollution. This supports the concept of targeting enforcement strategies [8]. However, their work relied on expensive chemical sensors than cost-effective visual detection. Knoll et al. developed large scale automated emission measurement systems using point sampling techniques [9]. Their

approach requires substantial infrastructure investments that limit widespread deployment potential.

New computer-based methods are a good way to handle this problem. Devi et al. proposed Internet-of-Vehicles networks for CO2 estimation using reinforcement learning. This demonstrates the scalability potential of intelligent systems [10]. Their approach however focused more on estimation than direct detection of high emission vehicles.

TABLE 1: Literature Review

S. No.	Source	Benefits	Limitations	Conclusions
2	Bernard et al. (2019) [2]	Remote sensing supports air quality management.	May not cover all applications comprehensively.	Highlight's role of RSS in emissions regulation.
3	TRUE Initiative (2018) [3]	Emphasizes real-world emissions data for policy.	Limited details on implementation strategies.	Demonstrates RSS effectiveness in urban areas.
7	Ghaffarpas and et al. (2022) [7]	High-emitter vehicles contribute disproportionately to pollution.	Focuses on specific vehicle subsets.	Supports targeted enforcement strategies.
18	Xie et al. (2024) [18]	Automatic hyperparameter Optimization improves emissions detection.	Requires integration with vehicle inspection stations.	Enhances adaptability of RSS models for high emitting vehicle detection.
19	Li et al. (2025) [19]	Uses deep CNNs for realtime pollution monitoring via surveillance cameras.	Dependent on accurate camera calibration.	Provides a cost-effective solution for emissions tracking in urban settings.
20	Knoll et al. (2024) [20]	Large-scale automated Emission measurement through point sampling.	Requires deployment in high-traffic areas for efficiency.	Effective for continuous vehicle emissions assessment.
21	Smit & Kingston (2019) [21]	Comparative analysis of multiple remote sensing instruments.	Variability in sensor performance across different environments.	Demonstrates the feasibility of integrating multiple sensing methods.
22	Borken-Kleefeld & Dallmann (2018) [22]	Highlights advantages of remote sensing over traditional emissions testing.	Implementation challenges due to policy constraints.	Supports adoption of remote sensing for regulatory enforcement.
23	Devi et al. (2024) [23]	IoV-based CO emission estimation using reinforcement learning.	Requireshigh computational resources.	Potentially scalable for smart city applications.
24	Zhang et al. (2021) [24]	Evaluates ammonia emissions using on-road remote sensing.	Limited to specific pollutant types.	Expands emissions monitoring beyond CO and NO.
25	Xu et al. (2021) [25]	Multi-feature fusion approach for identifying high-emission vehicles.	Requires extensive training data for optimal performance.	Demonstrates potential of machine learning in emissions detection.

26	Rauniyar et al. (2023) [26]	Combines noise and exhaust emissions monitoring for sustainability.	High initial deployment costs.	Supports intelligent transportation systems.
27	Rahman (2024) [27]	Systematic revie of satellite-based monitoring systems.	Challenges in data resolution and coverage.	Provides insights into the role of satellite technology in emissions regulation.

3 System Design and Architecture

3.1 YOLOv8 Architecture and Selection Rationale

We had selected YOLOv8 for this application based on three critical requirements: (a) real time processing capability, (b) accuracy in complex urban environments, and (c) deployment flexibility for edge computing scenarios [1]. YOLOv8 is the newest version in the YOLO series and works as a single step object detector. It incorporated several architectural improvements that make it particularly suitable for emission detection applications.

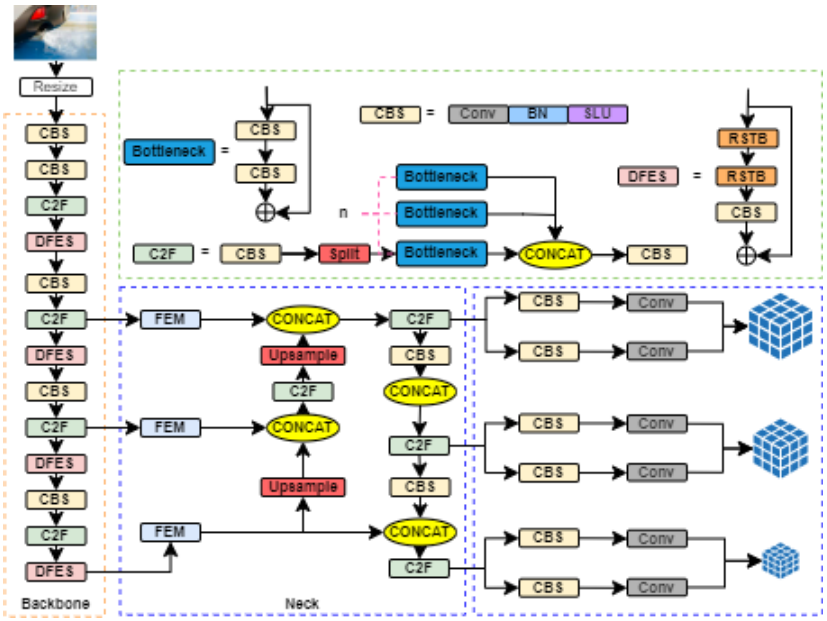


Fig. 1: YOLOv8 Architecture

From Figure 1, we can see that the YOLOv8 architecture consists of three primary components: (1) Backbone Network (CSPDarknet53) which serves as the feature extraction engine utilizing Cross Stage Partial connections to improve gradient flow during training. (2) Neck Network (PANet), facilitates multi-scale feature fusion. It enables the model to detect objects of varying sizes within the same image. (3) Detection Heads, these employed multiple detection heads operating at different scales, which allow for simultaneous detection of large objects (vehicles) and smaller, more transient objects (smoke emissions). Key improvements include the anchor-free design that eliminates predefined anchor boxes, instead predicting

bounding box coordinates directly. The design choice also improves detection flexibility for irregularly shaped objects like smoke plumes, which does not follow standard geometric shapes. Unlike previous work that attempts to quantify specific pollutants, we had focused more towards detecting visible emissions. This makes it possible to spot polluting vehicles right away and take action

3.2 Dataset Description and Preparation

Our research utilizes the Roboflow Smoke Vehicles Dataset. It consists of 1,034 images captured across diverse urban environments [11]. The dataset addresses the specific challenge of detecting vehicles emitting visible smoke, containing two primary object classes: (1) vehicles and, (2) smoke emissions. The dataset presents several characteristics that make it particularly suitable for training emission detection systems: images captured in various lighting conditions (daylight, dusk, artificial lighting), diverse urban environments (highways, city streets, traffic intersections), multiple vehicle types (passenger cars, trucks, buses, motorcycles), and varying emission intensities (light smoke to heavy plumes).
All images were standardized to 320x320 pixel resolution. This was done to optimize training efficiency while maintaining detection accuracy. We implemented several data augmentation techniques to improve model generalization including random rotation (±15 degrees), brightness and contrast adjustment, horizontal flipping, and random cropping.
We established a comprehensive evaluation framework using multiple performance metrics to assess YOLOv8's effectiveness in emission detection. Mean Average Precision (mAP) serves as the primary evaluation metric. Precision quantifies the model's ability to minimize false positive detections. Recall is used to measures the model's ability to identify all relevant objects.

4 Implementation and Experimental setup

4.1 Training Configuration

Model training was conducted in Google Colab, with T4 GPU. It provided sufficient computational resources for efficient training while being free of cost. For the training process we used adaptive learning rate scheduling and early stopping mechanisms to prevent overfitting.
The key training parameters included: batch size of 16 images, a learning rate of 0.01 with cosine annealing scheduling, a 100-training epoch limit with early stopping patience of 10 epochs, and an Adam optimizer with momentum of 0.9 and weight decay of 0.0005.

4.2 Comparative Analysis Framework

To validate our YOLOv8 models suitability for emission detection, we had conducted systematic comparisons with alternative approaches including one of YOLOv8's predecessor YOLOv5, the Faster R-CNN, and SSD. When we compared it with other models, we found YOLOv8 was better because it didn't need fixed anchor boxes and still found smoke accurately.
YOLOv8 demonstrated much better performance (77.7% mAP50) compared to YOLOv5's 73% mAP50. Especially when detecting irregular objects like smoke plumes. The inference speed comparison showed YOLOv8 processing images in 0.99 ms compared to YOLOv5's 1.2 ms average, representing a 17% performance improvement.

5 Result and Analysis

As we can see in Figure 2, our model demonstrated strong performance across all evaluation metrics. It achieved 77.7% mAP at IoU threshold 0.50, hence demonstrating strong overall detection capability suitable for real-world emission detection applications. The detection accuracy analysis revealed class specific performance variations. This was summarized in Table II. These results indicate that the vehicle detection approach proves more reliable than smoke detection, this could be likely due to vehicles being more consistent in visual characteristics compared to the highly variable appearance of emission plumes.

Table 2: YOLOv8 True Positive Values from Confusion Matrix

S. No.	Class	True Positive
1.	Smoke emitted	72.6%
2.	Vehicles	76.2%

The relationship between precision and recall is illustrated through the graphs in Figure 3. Our model achieved 76.3% precision and 74.4% recall, meaning it avoids many false positives and still catches most of the real emission events. The precision-recall curve shows a good balance across different thresholds, which helps in adapting the model for various deployment scenarios. We can see how well the model avoided false alarms in Figure 3a. Our model achieved 76.3% precision, indicating its effectiveness in minimizing false positive detections. It is important that the system doesn't make too many mistakes, or people might stop trusting it. That is why this result matters.

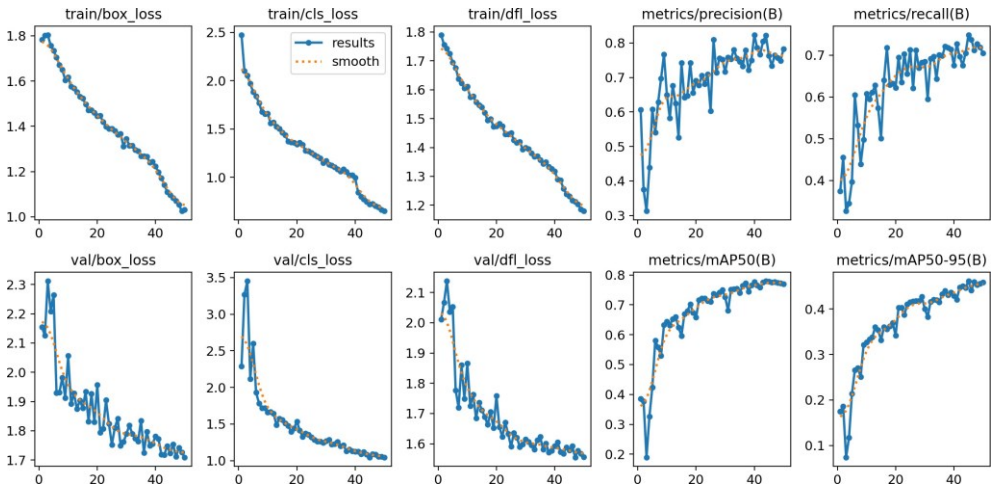
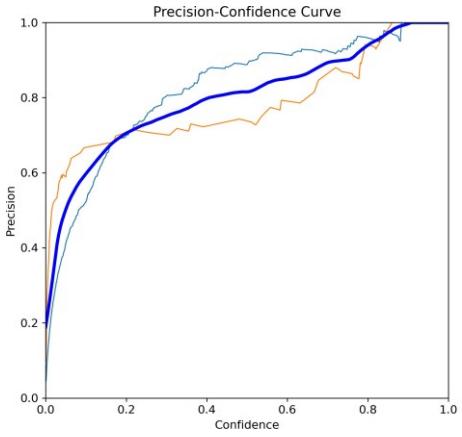


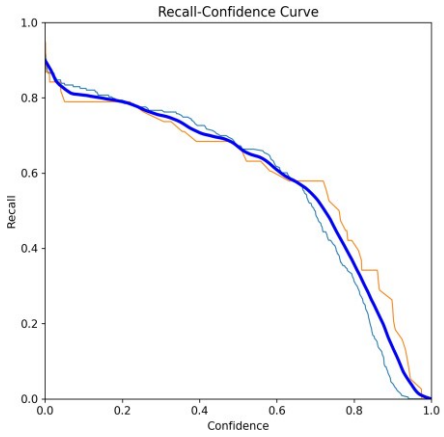
Fig. 2: YOLOv8's overall dataset evaluation metrics across training epochs

As shown in Figure 3b, our model achieved 74.4% recall. This showed the system's ability to identify majority of high emission vehicles present in the test dataset we used. The recall performance demonstrated that the system successfully detects approximately 75% of all emission, providing coverage for practical monitoring applications. The relationship between precision and recall is visualized in Figure 3c. It shows the optimal operating points for

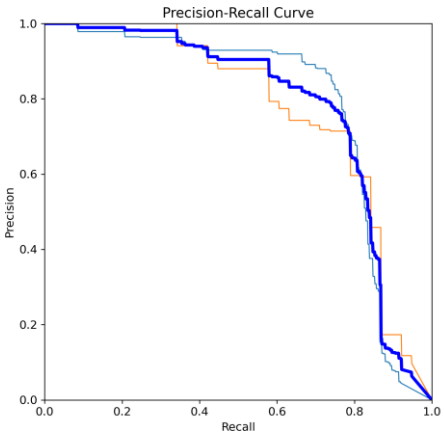
different deployment scenarios. The precision-recall curve demonstrates that our system maintains balanced performance across various confidence thresholds.



(a) Precision Curve



(b) Recall Curve



(c) Precision-Recall Curve

Fig. 3a-c: YOLOv8 model performance metrics across different thresholds

Table 3 summarizes the comprehensive performance evaluation results across different metrics and IoU thresholds. The model was able to process images with an average inference time of 0.99 ms using Google Colab's T4 GPU. This also demonstrates real-time processing capability for traffic monitoring applications. This performance enables processing of high-resolution video streams at standard frame rates without introducing significant latency. All These results show positive performance metrics that demonstrate our system's potential for integration into existing urban traffic monitoring networks. Our comparative analysis revealed that the model offers the optimal balance between detection accuracy and processing speed for emission detection applications

Table 3: Performance Metrics Summary

Metric	**Value**	**Class**

mAP50	77.7%	Overall
mAP50:95	46.1%	Overall
Precision	76.3%	Overall
Recall	74.4%	Overall
True Positive Rate	72.6%	Smoke
True Positive Rate	76.2%	Vehicle
Inference Time	0.99 ms	T4 GPU

. While Faster R-CNN achieved marginally higher accuracy (around 78% mAP50), its 200 ms processing time makes it impractical for real-time deployment. Our model's efficient architecture enables deployment across multiple monitoring points without requiring expensive com- putational infrastructure. This allows for scalability advantage and can support city wide implementation strategies that would be cost friendly with more computationally intensive approaches.

6 Discussion

To deploy automated emission detection systems in our urban environment would require careful consideration of multiple technical and operational factors. Based on what we tested, we found that YOLOv8 is a good choice to use the system in real cities.Edge computing deployment represents the most practical approach for city wide implementation. NVIDIA Jetson Nano's platform can provide sufficient computational power to run our model in real-time while maintaining energy efficiency suitable for traffic infrastructure deployment.Many cities already have cameras on the roads, so they can use this system without needing to buy too invest on new things. Improving these systems with emission detection capabilities would require minimal additional hardware investment. Especially with edge computing devices and network connectivity upgrades.

Emission detection in real world conditions face several environmental challenges that our current implementation addresses partially. Certain Weather conditions can obscure visual emissions. Rain, fog, and high humidity create can false positive de- tections. Our future iterations should incorporate weather data integration to adjust detection sensitivity based on environmental conditions.Another area of improvement is in urban environments. It presents complex visual backgrounds that can interfere with emission detection. Enhanced background subtraction techniques and analysis could help reduce false positive rates.

7 Conclusion and future work

Our research shows the practicality of automating high emission vehicle detection through computer vision technology. Specifically addressing the critical gap between environmental monitoring needs and available technological solutions. Our approach achieves detection performance suitable for real-world deployment while maintaining cost-effectiveness and scalability. This project helps in a few ways, it shows that we can use cameras to find

polluting cars without expensive tools. The implementation is also able to demonstrate that modern object detection technology can successfully address environ- mental monitoring challenges. The achieved performance metrics: 76.3% precision, 74.4% recall, and 0.99 ms inference time establish a foundation for practical deployment while identifying specific areas for continued improvement. Future research includes but does not limit to integration of pollutant quantification to enhance detection capabilities. System integration with traffic management and enforcement automation represents another important aspect. This method can also help in other areas like monitoring traffic or watching for other environmental problems.

References

1. M. Yaseen, What is yolov8: An in-depth exploration of the internal features of the next-generation object detector, *arXiv preprint arXiv:2408.15857*, (2024).
2. Wang et al., Cspnet: A new backbone that can enhance learning capability of cnn, in *CVPR*, (2020).
3. Y. Bernard et al., Worldwide use of remote sensing to measure motor vehicle emissions, *The International Council on Clean Transportation, White Paper*, Aug (2019). [Online]. Available: https://theicct.org/publication/worldwide-use-of-remote-sensing-to-measure-motor-vehicle-emissions/
4. H. Xie, Y. Zhang, Y. He, K. You, P. Dai, B. Fan, others, and W. Liu, On-road high-emitting vehicle identification by an automatic hyperparameter optimization model based on a remote sensing system, *Measurement*, 225, 113938, (2024).
5. M. Li, Y. Tang, K. Wu, and H. Cheng, Autonomous vehicle pollution monitoring: An innovative solution for policy and environmental management, *Transportation Research Part D: Transport and Environment*, 139, 104542, (2025).
6. Y. Bernard and J. German, Remote sensing of vehicle emissions: A tool to support air quality management, *The International Council on Clean Transportation, Briefing Paper*, Dec (2018). [Online]. Available: https://theicct.org/sites/default/files/publications/ICCT remote-sensing brief 201812.pdf
7. J. Borken-Kleefeld and T. Dallmann, Remote sensing of motor vehicle exhaust emissions, *The International Council on Clean Transportation, Tech. Rep.*, (2018).
8. O. Ghaffarpasand, K. Ropkins, D. C. S. Beddows, and F. D. Pope, Detecting high emitting vehicle subsets using emission remote sensing systems, *Sci Total Environ*, 858(Part 2), 159814, (2023). [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0048969722069145
9. M. Knoll, M. Penz, H. Juchem, C. Schmidt, D. Pöhler, and A. Bergmann, Large-scale automated emission measurement of individual vehicles with point sampling, *Atmos. Meas. Tech.*, 17, 2481–2505, (2024).
10. A. S. Devi, M. M. J. Britto, Z. Fang, R. Gopan, P. S. Jassal, M. M. Qazzaz, others, and F. M. Al-Sallami, Internet-of-vehicles network for CO_2 emission estimation and reinforcement learning-based emission reduction, *IEEE Access*, (2024).
11. Roboflow, Smoke vehicles dataset, (2024), accessed: Dec. 1, 2024. [Online]. Available: https://universe.roboflow.com/alpha-ai-nwrrb/smoke-vehicles
12. European Commission, Using remote sensing technology to measure vehicle emissions, *CORDIS EU Research Results*, (2023). [Online]. Available: https://cordis.europa.eu/article/id/446410-using-remote-sensing-technology-to-measure-vehicle-emissions

13. The Real Urban Emissions Initiative (TRUE), Using remote sensing technology to measure real-world vehicle emissions, *TRUE Initiative*, (2024), accessed: Dec. 2, 2024. [Online]. Available: https://www.trueinitiative.org
14. Clean Air Fund, Vehicle pollution emissions, *Clean Air Fund News*, (2024). [Online]. Available: https://www.cleanairfund.org/news-item/ vehicle-pollution-emissions/
15. Opus Group, Remote sensing for vehicle inspection, *Opus Vehicle Inspection*, (2024). [Online]. Available: https://www.opus.global/vehicle-inspection/ remote-sensing/
16. Khaleej Times, Uae: New system to measure vehicle emissions in abu dhabi using latest technology, *Khaleej Times*, (2024). [Online]. Available: https://www.khaleejtimes.com/uae/environment/uae-new-system-to-measure-vehicle-emissions-in-abu-dhabi-using-latest-technology
17. G. Jocher et al., Ultralytics yolov8: A state-of-the-art object detection model, *GitHub repository*, (2023). [Online]. Available: https://docs.ultralytics.com/models/yolov8/
18. Yolov8 metrics: Unveiling key insights, (2024). [Online]. Available: https://yolov8.org/unveiling-the-secrets-of-yolov8-metrics/
19. How to evaluate yolov8 model: A comprehensive guide, (2024). [Online]. Available: https://yolov8.org/how-to-evaluate-yolov8-model/
20. Liu et al., Path aggregation network for instance segmentation, in *CVPR*, (2018).
21. Lin et al., Feature pyramid networks for object detection, in *CVPR*, (2017).
22. Hosang et al., Learning non-maximum suppression, in *CVPR*, (2017).
23. R. Smit and P. Kingston, Measuring on-road vehicle emissions with multiple instruments including remote sensing, *Atmosphere*, 10(9), 516, (2019).
24. Q. Zhang, N. Wei, C. Zou, and H. Mao, Evaluating the ammonia emission from in-use vehicles using on-road remote sensing test, *Environ Pollut*, 271, 116384, (2021).
25. Z. Xu, R. Wang, R. Wang, C. Zhang, and X. Xia, Unsupervised identification of high-emitting mobile sources based on multi-feature fusion, in *2021 China Automation Congress (CAC). IEEE*, 652–657, (2021).
26. A. Rauniyar, T. Berge, A. Kuijpers, P. Litzinger, B. Peeters, E. V. Gils, others, and J. E. Håkegård, Nemo: Real-time noise and exhaust emissions monitoring for sustainable and intelligent transportation systems, *IEEE Sensors J*, (2023).
27. S. M. Rahman, A systematic literature review of satellite-based monitoring systems in road transportation: Techniques, applications, and challenges, *Frontiers in Applied Engineering and Technology*, 1(01), 286–303, (2024).