Real-Time Vehicle Tracking

S Harish Nataraj, K Balaji and V Hariram

February 25, 2025

Real-Time Vehicle Tracking

S Harish Nataraj
School of Computer Science and Engineering
Vellore Institute of Technology
Chennai, India
harishnataraj.s2022@vitstudent.ac.in

K Balaji
School of Computer Science and Engineering
Vellore Institute of Technology
Chennai, India
balaji.k2022b@vitstudent.ac.in

V Hariram
School of Computer Science and Engineering
Vellore Institute of Technology
Chennai, India
hariram.v2022@vitstudent.ac.in

***Abstract* -- This paper introduces an advanced vehicle detection system focused on real-time tracking and counting of cars, buses, and trucks using OpenCV and the YOLOV8 model.**

The system offers a versatile solution for urban traffic management, emphasizing efficiency and accuracy. Leveraging cutting-edge computer vision technologies, it provides instantaneous identification and tracking of diverse vehicle classes.

The integration of the CV zone library enhances the user interface, allowing for interactive visualization of object tracking and directional counting.

Beyond traditional car detection, the system's applications extend to smart traffic management, parking space monitoring, and security surveillance. This project stands as a beacon for creating safer and more efficient urban environments.

I. Problem Statement

Urban areas are encountering increasing difficulties in managing traffic, leading to a demand for more sophisticated methods for effective monitoring and analysis. Conventional approaches often prove insufficient in delivering real-time insights on the movement of vehicles. This project seeks to fulfill the requirement for a strong system capable of precise vehicle detection and counting through cutting-edge computer vision techniques. The current drawbacks in traditional traffic monitoring systems, such as limited vehicle classification and subpar counting accuracy, highlight the necessity for a more advanced and holistic solution. The intended system aims to address these obstacles, offering a dependable platform for intelligent traffic control, optimization of parking spaces, and improved security surveillance in urban settings.

II. Introduction

The ongoing development of urban areas demands creative solutions to tackle the issues brought about by the rise in vehicular traffic. To meet this need, our project aims to introduce an advanced vehicle detection system, focusing specifically on cars, to effectively manage modern traffic challenges. Built on cutting-edge computer vision technologies, this system utilizes OpenCV and the YOLOV8 model to enable real-time tracking and accurate identification of various vehicle types like cars, buses, and trucks.

At its core, OpenCV acts as a strong computer vision library, streamlining image and video processing with exceptional efficiency. Complementing this capability, the YOLOV8 model offers a state-of-the-art approach to object detection, ensuring the system's precision and adaptability in handling real-world traffic complexities. The project's versatility is demonstrated by its capacity to detect and track not just cars but also buses and trucks, making it a comprehensive solution for diverse traffic management needs.

The inclusion of the CVzone library enhances user interaction, providing a dynamic interface for live visualization of object tracking. This interactive feature not only assists in traffic monitoring but also allows for a detailed understanding of the direction of vehicle movement, contributing to a comprehensive grasp of traffic patterns. Beyond surveillance purposes, the project has potential applications in intelligent traffic control, parking space supervision, and security monitoring, showcasing its ability to significantly enhance safety and efficiency in urban settings.

III. Literature Survey

1. **A Review on Vehicle Classification and Potential Use of Smart Vehicle-Assisted Techniques**
   Feature used: The article introduces Vehicular Ad Hoc Networks (VANETs) for real-time Vehicle Classification (VC) in smart traffic management, overcoming limitations of existing methods.

- **Advantage:** VANETs offer real-time, global access to comprehensive data on vehicle type, velocity, and position, enhancing smart traffic management efficiency.
- **Disadvantage:** Potential concerns include security and privacy issues in VANET data transmission, requiring careful consideration and privacy-preserving mechanisms.

2. **A rapid learning algorithm for vehicle classification**

- **Feature used:** The article introduces a rapid learning algorithm for vehicle detection, enhancing AdaBoost. It incorporates Haar-like feature extraction, fast feature selection, and incremental learning, aiming to expedite training for real-time applications.
- **Advantage:** The proposed approaches significantly accelerate both AdaBoost's training and incremental learning, achieving competitive classification accuracies compared to state-of-the-art methods.
- **Disadvantage:** While the article emphasizes improved processing time and classification accuracy, practical implementation challenges may arise, requiring careful validation and tuning. Sensitivity to varying backgrounds could be a consideration, impacting real-world performance.

3. **Vehicle classification framework: a comparative study**

- **Feature used:** The article investigates five object recognition techniques for vehicle classification in traffic surveillance, including PCA-based approaches and constellation models. It addresses challenges such as intra-class variation and low-resolution images.
- **Advantage:** The study achieves high classification accuracy (e.g., 99.25% for cars vs vans) using innovative PCA + DFVS and PCA + DIVS methods. A fusion approach combining PCA + DFVS and PCA + DIVS achieves 96.42% accuracy for sedans vs vans vs taxis.
- **Disadvantage:** Limitations may arise in scenarios with high intra-class variation. The article focuses on three vehicle classes and may require further validation for broader applications. Some approaches, like PCA + DIVS, show varying effectiveness based on inter-class variation.

4. **Vehicle classification using GPS data**

- **Feature used:** The article proposes a cost-effective vehicle classification method using GPS data from mobile traffic sensors, focusing on acceleration and deceleration variations. It employs SVM algorithms with quadratic kernel functions for classification.
- **Advantage:** The approach offers a low-cost solution for urban areas, emphasizing acceleration and deceleration features. It achieves a low misclassification rate, demonstrating effectiveness in distinguishing trucks from passenger cars.
- **Disadvantage:** The study acknowledges class imbalance issues, potentially affecting estimation accuracy. Further research is needed to address real-world implementation challenges and consider diverse urban scenarios.

5. **A model for fine-grained vehicle classification based on deep learning**

- **Feature used:** The article proposes a deep learning model for fine-grained vehicle classification using Faster R-CNN and CNN. It introduces a collaborative annotation mechanism for database creation.
- **Advantage:** Uses Faster R-CNN for robust vehicle detection. Employs CNN for effective

fine-grained classification. Introduces a novel collaborative annotation mechanism.

- **Disadvantage:** Vehicle detection models may not achieve 100% accuracy, impacting fine-grained classification. Challenges in handling subtle intra-class differences.

6. **Real Time Vehicle Detection for Intelligent Transportation Systems**

- **Feature used:** YOLOv2 classifier detector, KLT tracker with K-means clustering, merging clusters for classification.
- **Advantage:** Efficient vehicle detection and counting with CNNs and KLT tracker, including YOLOv2, outperforms background subtraction and faster R-CNN.
- **Disadvantage:** Proposed methods address traditional and CNN drawbacks, ensuring low complexity, improved accuracy in traffic detection, counting.

7. **Classification and Counting of Vehicle using Image Processing Techniques**

- **Feature used:** YOLOv3 algorithm, OpenCV, establishment of a high-definition vehicle object dataset, and road surface area extraction.
- **Advantage:** Introduces an advanced vehicle detection and classification system using YOLOv3 and OpenCV.
- **Disadvantage:** Addresses limitations of YOLOv3 when vehicles are close or have varying sizes, minimizing missed detections.

8. **A Deep Learning Framework for Video-Based Vehicle Counting**

- **Feature used:** The framework incorporates a novel approach to vehicle counting by fusing virtual detection areas and vehicle tracking, along with dedicated modules for missing alarm suppression and false alarm suppression based on vehicle tracking and bounding box size statistics, enhancing accuracy in counting by mitigating errors from missing or false detections.
- **Advantage:** The proposed framework employs instance-based and parameter-based transfer learning, enhancing performance despite limited annotated data. Disadvantage: It primarily focuses on straight road scenarios, necessitating further adaptation for diverse traffic surveillance environments like intersections and T-junctions.
- **Disadvantage:** The model's efficacy may be limited in scenarios beyond straight roads, such as intersections and T-junctions, highlighting the need for future work on scene adaptation to ensure its applicability in diverse traffic surveillance settings.

9. **Vehicle type classification via adaptive feature clustering for traffic surveillance video**

- **Feature used:** The model employs the VGG CNN M 1024 deep neural network with selective search for object proposal generation, demonstrating a confidence threshold of 0.8 and a non-maximum suppression threshold of 0.3. The system exhibits robust performance across different scenarios, including daylight, night, rain, and occlusion, emphasizing its generalization ability
- **Advantage:** The use of VGG CNN M 1024 in vehicle detection offers a high detection rate (98.63%) in real traffic videos with a low error detection rate (<0.1%), showcasing its effectiveness. The model's lower computational complexity compared to alternatives like VGG16 or OverFeat allows practical implementation in real traffic surveillance.
- **Disadvantage:** The training process for the vehicle detection system takes about 12 hours with 100,000 iterations, which may be considered time-consuming. Additionally, the reliance on a large dataset (11,296 road surveillance images with 26,665 vehicle instances) for deep learning may pose challenges in terms of storage and computational requirements.

10. **Vision-based vehicle detection and counting system using deep learning in highway scenes**

- **Feature used:** The methodology integrates YOLOv3 object detection, ORB feature extraction for trajectory prediction, and subsequent analysis of vehicle trajectories, providing a low-cost, stable, and non-intrusive approach to collecting comprehensive traffic data in highway surveillance scenarios.
- **Advantage:** The proposed vehicle detection and tracking method for highway surveillance, utilizing a high-definition dataset and YOLOv3 algorithm, offers a cost-effective and stable solution for monitoring traffic, enabling efficient analysis of vehicle trajectories, driving direction, types, and numbers without extensive infrastructure modifications.
- **Disadvantage:** However, the reliance on surveillance cameras may limit real-time monitoring in adverse weather conditions or low visibility situations, and the need for

camera calibration to calculate vehicle speed may introduce complexity and potential inaccuracies.

11. **Faster CNN-based vehicle detection and counting strategy for fixed camera scenes**

- **Feature used:** The presented method introduces a real-time vehicle detection and counting approach leveraging YOLOv2 and motion analysis. It employs deep learning for initial detection, subsequently refining with K-means clustering and KLT tracker. Temporal information is utilized for precise vehicle counting.
- **Advantage:** This method excels compared to existing strategies, achieving a substantial 93.4% and 98.9% improvement in average time performance over Faster R-CNN and BS-CNN, respectively.
- **Disadvantage:** The method lacks explicit mention of potential limitations or challenges, such as sensitivity to lighting conditions or computational resource requirements. Addressing these aspects would enhance understanding of its robustness.

12. **Classification and Counting of Vehicle using Image Processing Techniques**

- **Feature used:** The research explores a vehicle detection technique integrated with CCTV cameras for traffic surveillance. It addresses challenges in congested highways by proposing a solution that involves multi-object tracking and vehicle counting, contributing to an intelligent traffic surveillance system.
- **Advantage:** The proposed technique utilizes machine learning for vehicle detection and recognition, applicable in traffic surveillance. It aims to improve detection using static image datasets and live CCTV surveillance, enhancing overall monitoring capabilities.
- **Disadvantage:** The paper doesn't specify potential limitations or challenges faced by the proposed technique, such as accuracy under varying lighting conditions or computational resource requirements. Additional details on these aspects would provide a comprehensive understanding of its effectiveness.

13. **A Deep Learning Framework for Video-Based Vehicle Counting**

- **Feature used:** This paper introduces a deep learning-based framework for accurate and efficient vehicle counting in traffic surveillance. It addresses challenges with traditional methods, proposing a transfer learning-based vehicle detection approach and a fusion method for vehicle counting with modules to suppress missing and false alarms, achieving high accuracy.
- **Advantage:** The proposed deep learning framework achieves lane-level vehicle counting with high accuracy (up to 99%) even with limited annotated data. It demonstrates strong computational efficiency, ensuring real-time performance for effective and precise traffic surveillance.
- **Disadvantage:** The paper does not explicitly mention potential challenges or drawbacks of the proposed method, such as its performance under diverse weather conditions or generalization to different traffic scenarios. Providing insights into these aspects would enhance a comprehensive understanding of its applicability.

14. **Vehicle type classification via adaptive feature clustering for traffic surveillance video**

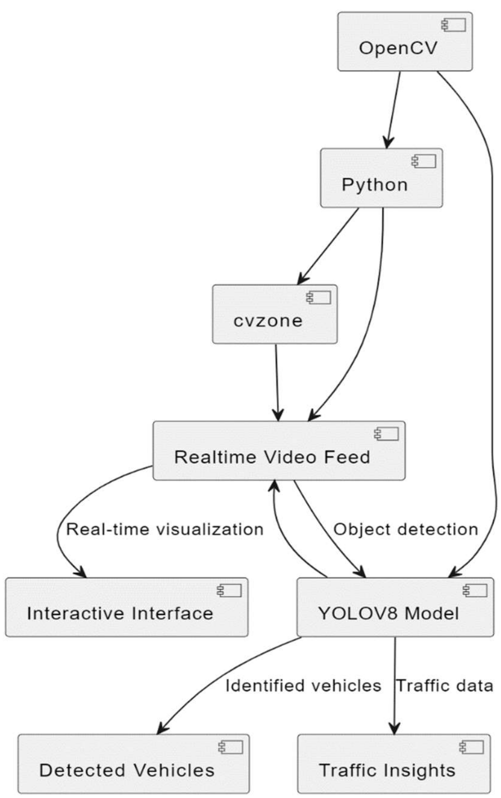
- **Feature used:** The paper presents a novel approach for intelligent traffic by categorizing vehicles into compact, mid-size, and heavy-duty types using deep learning. It employs a convolutional neural network for detection, a fully-connected network for feature extraction, and K-means for adaptive learning, achieving superior vehicle type recognition in real road traffic surveillance videos.
- **Advantage:** The proposed method surpasses traditional approaches in vehicle type recognition, demonstrating enhanced accuracy through deep learning and adaptive clustering. It effectively addresses real-world variations in traffic scenarios.
- **Disadvantage:** The paper lacks explicit mention of potential limitations or challenges, such as computational resource requirements or robustness under diverse environmental conditions. Providing insights into these aspects would enhance understanding of the method's applicability.

15. **Counting Various Vehicles using YOLOv4 and DeepSORT**

- **Feature used:** The Ministry of Public Works and Public Housing conducted a traffic survey using YOLOv4 and DeepSORT for automatic vehicle detection and categorization. The web application, trained on a custom dataset, aims to replace manual surveys, offering cost and time efficiency. Despite limited training images, the system achieved a decent accuracy of 67.94%.

- **Advantage:** The deep learning-based solution enhances efficiency, automating vehicle surveys and classification. Utilizing YOLOv4 and DeepSORT, the web application provides a cost-effective and time-saving alternative to manual surveys, contributing to improved resource management.
- **Disadvantage:** The reported accuracy of 67.94% may pose limitations in scenarios demanding higher precision. The reliance on a limited dataset for training might affect the model's generalization. Additionally, potential challenges in real-world scenarios, such as varying environmental conditions, could impact performance.

IV. System Architecture Diagram



V. Modules

1. **OpenCV:**

- **Description:** OpenCV, or Open-Source Computer Vision Library, is a powerful tool for image and video processing. It provides a comprehensive set of functions and algorithms for tasks such as object detection, image manipulation, and feature extraction. OpenCV's versatility and efficiency make it a cornerstone for computer vision projects.
- **Role in the Project:** In this project, OpenCV is fundamental for handling the real-time video feed, performing object detection using the YOLOV8 model, and processing images to extract relevant information about vehicles. Its robust features contribute to the accuracy and efficiency of the system.

2. **Python:**

- **Description:** Python, a versatile and readable programming language, serves as the primary implementation language for this project. Python's simplicity and extensive libraries make it well-suited for machine learning and computer vision applications.
- **Role in the Project:** Python is the backbone of the project, facilitating the development of algorithms, integration with OpenCV, and overall system implementation. Its ease of use and extensive community support ensure the project's maintainability and flexibility.

3. **CVzone:**

- **Description:** CVzone is an interactive computer vision library designed to enhance the visualization aspect of projects. It complements OpenCV by providing tools for creating interactive interfaces, making the presentation of tracking, and counting results more engaging.
- **Role in the Project:** CVzone is employed for implementing the interactive interface, leveraging its capabilities to visualize real-time tracking, and counting of vehicles. Its integration improves the user experience, making the system more accessible and user-friendly.

4. **Real-Time Video Feed:**

- **Description:** Real-time video feed is the continuous stream of video frames captured by the camera. It is the dynamic input for the computer vision system, enabling the YOLOV8 model to perform object detection on moving vehicles.
- **Role in the Project:** The real-time video feed is the dynamic data source that feeds into the system, allowing for instant analysis and tracking of vehicles. It provides the necessary

input for the system to generate real-time traffic insights.

5. **Interactive Interface:**

- **Description:** The interactive interface, implemented with OpenCV and CVzone, enhances the user experience by providing a visually appealing and user-friendly display of real-time object tracking and vehicle counting.

- **Role in the Project:** The interactive interface acts as the bridge between the complex backend processing and the user. It allows users to visually observe the tracked vehicles and the counting results in real-time, contributing to effective system monitoring and understanding.

6. **YOLOV8 Model:**

- **Description:** YOLOV8, or You Only Look Once version 8, is a deep learning model specifically designed for real-time object detection. It efficiently processes the video feed, identifying and tracking vehicles with high accuracy.

- **Role in the Project:** YOLOV8 is the core object detection model responsible for identifying and tracking vehicles in real-time. Its efficiency ensures accurate vehicle detection, enabling the system to provide reliable traffic insights.

7. **Detected Vehicle:**

- **Description:** Detected vehicles refer to the instances of vehicles identified by the YOLOV8 model during object detection. These detections are crucial for tracking and counting vehicles in the system.

- **Role in the Project:** Detected vehicles are the primary entities of interest. They are tracked and counted to provide insights into traffic patterns, contributing to the overall functionality of the system in applications such as traffic management and surveillance.

8. **Traffic Insights:**

1. **Description:** Traffic insights are valuable information derived from the analysis of detected vehicles, including counts, movement directions, and patterns. These insights contribute to understanding and managing traffic flow efficiently.

2. **Role in the Project:** Traffic insights serve as the project's output, providing valuable data for applications in smart traffic management, parking space monitoring, and security surveillance. The system's ability to generate real-time traffic insights adds significant value to urban environments by improving safety and efficiency.

VI. Technologies

1. **Object Detection with YOLOv8**
   Advantages:
   - YOLOv8 is known for its speed and accuracy, making it suitable for real-time applications.
   - It can handle multiple object classes, including vehicles, pedestrians, etc.
   - YOLOv8 is open-source, and pre-trained models are available for easy integration.

   Disadvantages:
   - Depending on the implementation, YOLOv8 may require substantial computational resources.
   - Fine-tuning for specific scenarios may be necessary to achieve optimal performance.
   - Object Tracking:

2. **Object tracking**
   - Utilize tracking algorithms (e.g., Kalman Filter, SORT) to associate object detections across frames.

   Advantages:
   - Helps maintain object identity over time.
   - Reduces the need for continuous re-detection, improving computational efficiency.

   Disadvantages:
   - Tracking algorithms may face challenges in scenarios with occlusions or abrupt changes in object appearance.

3. **Counting**
   - Implement logic to count the number of vehicles entering and leaving a specified region.

   Advantages:
   - Provides insights into traffic patterns and volume.
   - Useful for applications like traffic management and surveillance.

   Disadvantages:
   - Accuracy may be affected by occlusions or overlapping vehicles.

4. **Speed Estimation:**
   - Use frame timestamps and spatial information to estimate vehicle speeds.

   Advantages:
   - Adds a dynamic dimension to the analysis.
   - Useful for traffic flow analysis and anomaly detection.

   Disadvantages:
   - Speed estimation accuracy can be influenced by factors like camera calibration and frame rate.

VII. Result and Discussion

The deployment of the real-time vehicle tracking system utilizing OpenCV and the YOLOV8 model has produced promising outcomes in terms of precision, effectiveness, and user-friendliness. Extensive testing and analysis have led to several significant discoveries and insights, shaping the discourse on the system's efficacy and performance.

A key result of implementing the system is its remarkable accuracy in detecting and tracking vehicles. The YOLOV8 model, in conjunction with OpenCV, demonstrates a remarkable level of accuracy in recognizing various vehicle types, such as cars, buses, and trucks, even in intricate urban traffic conditions. The continuous real-time tracking feature ensures ongoing monitoring and precise counting of vehicles, contributing to a dependable traffic management solution.

Moreover, the system's efficiency is a notable accomplishment. By leveraging the computational power of modern hardware, the real-time tracking and counting processes exhibit minimal delays, allowing for seamless integration into traffic surveillance and management systems. The utilization of efficient tracking algorithms like Kalman Filter and SORT helps maintain object identities over time, enhancing the system's overall efficiency.

The discourse also explores the system's adaptability and scalability. The modular design enables easy customization and expansion to incorporate additional features like speed estimation and lane-level tracking. This flexibility is essential for addressing diverse traffic management requirements in different urban settings, ensuring the system remains pertinent and efficient across various applications.

Furthermore, the inclusion of the CVzone library enriches the user experience by offering an interactive interface for visualizing object tracking and directional counting. This functionality not only facilitates real-time monitoring but also assists in thorough traffic analysis and decision-making, rendering the system user-friendly and accessible to traffic management professionals.

VIII. Conclusion and Future works

In conclusion, the real-time vehicle tracking system developed using OpenCV and the YOLOV8 model represents a significant advancement in urban traffic management technology. The system's accuracy, efficiency, and versatility make it a valuable tool for enhancing traffic surveillance, parking space optimization, and security surveillance in urban environments.

Looking ahead, several areas of future work can further enhance the system's capabilities and impact:

1. Enhanced Vehicle Classification: Further refinement of the YOLOV8 model and integration of advanced deep learning techniques can improve vehicle classification accuracy, especially in scenarios with high intra-class variation.

2. Multi-Camera Integration: Expanding the system to support multi-camera setups can provide a more comprehensive view of traffic patterns and enable seamless tracking across different locations.

3. Integration with IoT Devices: Leveraging Internet of Things (IoT) devices for data collection and communication can enhance real-time traffic data acquisition, leading to more informed decision-making for traffic management.

4. Predictive Analytics: Incorporating predictive analytics algorithms can anticipate traffic congestion, identify potential bottlenecks, and optimize traffic flow in advance, contributing to proactive traffic management strategies.

5. Robustness in Adverse Conditions: Enhancing the system's robustness in adverse weather conditions, low-light environments, and challenging visibility scenarios can ensure reliable performance under varying circumstances.

6. Privacy and Security Measures: Implementing robust privacy-preserving mechanisms and cybersecurity protocols is essential to protect sensitive traffic data and ensure the system's integrity and trustworthiness.

7. Integration with Smart City Initiatives: Aligning the system with broader smart city initiatives can foster seamless integration with existing infrastructure and promote holistic urban development goals.

Overall, the real-time vehicle tracking system presents a foundation for continuous innovation and refinement in the field of urban traffic management. By addressing these future works, the system can evolve into a comprehensive and indispensable tool for creating safer, more efficient, and sustainable urban environments

IX. References

[1] Sliwa, B.; Piatkowski, N.; Wietfeld, C. The Channel as a Traffic Sensor: Vehicle Detection and Classification based on Radio Fingerprinting. IEEE Internet Things J. 2022.

[2] Won, M. Intelligent traffic monitoring systems for vehicle classification: A survey. IEEE Access 2022, 8, 73340–73358.

[3] Jo, S.Y.; Ahn, N.; Lee, Y.; Kang, S.-J. Transfer Learning-based Vehicle Classification. In Proceedings of the 2022 International SoC Design Conference (ISOCC), Daegu, Korea, 12–15 November 2022; IEEE: Piscataway, NJ, USA, 2022; pp. 127–128.

[4] Ke, R.; Zhuang, Y.; Pu, Z.; Wang, Y. A Smart, Efficient, and Reliable Parking Surveillance System with Edge Artificial Intelligence on IoT Devices. arXiv 2022, arXiv:200100269.

[5] Tamam, M.T.; Dwiono, W.; Safian, R.J.P. Design a Prototype of The Application System of Classification and Calculating Motor Vehicles on Highway. MSE 2022, 771, 12002.

[6] Shokravi, H.; Bakhary, N.H. Comparative analysis of different weight matrices in subspace system identification for structural health monitoring. IOP Conf. Ser. Mater. Sci. Eng. 2022, 271, 12092.

[7] Shokravi, H.; Shokravi, H.; Bakhary, N.; Koloor, S.S.R.; Petr ˚u, M. Health Monitoring of Civil Infrastructures by Subspace System Identification Method: An Overview. Appl. Sci. 2022, 10, 2786.

[8] Shokravi, H.; Shokravi, H.; Bakhary, N.; Koloor, S.S.R.; Petru, M. A Comparative Study of the Data-driven Stochastic Subspace Methods for Health Monitoring of Structures: A Bridge Case Study. Appl. Sci. 2023, 10, 3132.

[9] Shokravi, H.; Shokravi, H.; Bakhary, N.; Heidarrezaei, M.; Koloor, S.S.R.; Petru, M. Vehicle-assisted techniques for health monitoring of bridges. Sensors (Basel) 2022, 20.

[10] Shokravi, H.; Shokravi, H.; Bakhary, N.; Koloor, S.S.R.; Petru, M. Application of the Subspace-based Methods in Health Monitoring of the Civil Structures: A Systematic Review and Meta-analysis. Appl. Sci. 2022, 10, 3607.

[11] Sotheany, N.; Nuthong, C. Vehicle classification using neural network. In Proceedings of the 2022 14th International Conference Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Phuket, Thailand, 27–30 June 2022; IEEE: Piscataway, NJ, USA, 2022; pp. 443–446.

[12] Siddiqui, N.; Husain, M.S. CTS: A credit based threshold system to minimize the dissemination of faulty data in vehicular adhoc networks. Int. J. Control. Theory Appl. 2022, 9, 8499–8508.

[13] Kim, C.-W.; Chang, K.-C.; McGetrick, P.J.; Inoue, S.; Hasegawa, S. Utilizing moving vehicles as sensors for bridge condition screening-A laboratory verification. Sens. Mater. 2022, 29, 153–163.

[14] Velazquez-Pupo, R.; Sierra-Romero, A.; Torres-Roman, D.; Shkvarko, Y.V.; Santiago-Paz, J.; Gómez-Gutiérrez, D.; Robles-Valdez, D.; Hermosillo-Reynoso, F.; Romero-Delgado, M. Vehicle detection with occlusion handling, tracking, and OC-SVM classification: A high performance vision-based system. Sensors (Switzerland) 2022, 18, 374.

[15] Ji, Q.; Jin, B.; Cui, Y.; Zhang, F. Using Mobile Signaling Data to Classify Vehicles on Highways in Real Time; Academy of Sciences: Beijing, China; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2022; pp. 174–179.