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Towards an AI-based Transportation Monitoring System using Campus Video Footage: Early Experiments in Vehicle Detection and Tracking

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ABSTRACT

This paper presents early experimental results towards developing an AI-based transportation monitoring system using campus video footage at Universiti Malaya. Manual traffic monitoring is inefficient, and the lack of automated systems makes real-time tracking and carbon emission estimation particularly challenging in campus environments. The primary objective is to develop a system capable of accurately detecting and tracking vehicles, identifying vehicle types, recognizing license plates, and estimating vehicle speeds. This data, particularly vehicle speed, is crucial for subsequent estimation of carbon emissions, a key parameter for comprehensive campus transportation monitoring. Our methodology involved capturing video data at various strategic locations within the Universiti Malaya campus using a single, fixed handheld camera. We employed a robust AI pipeline leveraging YOLOv8 for vehicle detection and tracking, a custom-trained YOLO model for license plate detection, and EasyOCR for optical character recognition of license plates. Preliminary experiments demonstrate the system's ability to track individual vehicles, classify them by type, and extract license plate information, along with real-time speed estimation. Challenges related to camera resolution, placement trade-offs for optimal detection, and deployment logistics were identified. This work lays the foundation for a more comprehensive, real-time transportation monitoring system, with future efforts focusing on improving accuracy, optimizing for edge deployment, and integrating multi-camera data for enhanced environmental impact assessment.

1. Introduction

Urban and campus environments face increasing challenges related to transportation, including traffic congestion, safety concerns, and environmental impact, particularly carbon emissions [1,2]. Traditional methods of traffic monitoring often involve manual counts or expensive, fixed sensor installations, which may lack the granularity or flexibility required for dynamic analysis [3,4]. The advent of artificial intelligence (AI), particularly computer vision techniques, offers promising avenues for developing more efficient, scalable, and intelligent transportation monitoring systems

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[5]. Such systems can provide valuable insights into traffic flow patterns, vehicle demographics, and enable data-driven decision-making for urban planning and environmental management.

The field of AI-based transportation monitoring has seen significant advancements in recent years, largely driven by breakthroughs in deep learning and computer vision [6]. Object detection models such as You Only Look Once (YOLO) [7] have demonstrated remarkable performance in real-time vehicle detection and classification [8]. Similarly, vehicle tracking algorithms, often integrated with detection models, are crucial for understanding vehicle trajectories and behaviors. License plate recognition (LPR) systems [9,10], commonly relying on a combination of object detection for plate localization and Optical Character Recognition (OCR) for text extraction, are well-established for various applications, including access control and law enforcement [11]. Crucially, the estimation of carbon emissions from vehicular traffic is a well-researched area, with established models correlating vehicle speed with emission rates [12-14].

Despite these advancements, the direct application and comprehensive integration of these AI techniques into a cohesive, campus-specific transportation monitoring system, especially with a direct link to environmental parameters like carbon emissions, remains an area with significant research gaps. Existing solutions often focus on isolated aspects (e.g., only traffic counting or only LPR) or are designed for broader urban scales, which may not adequately address the unique operational and environmental monitoring needs of a contained university campus [15-17]. Furthermore, many studies do not fully explore the practical challenges [18] of data collection in varied campus environments and the trade-offs involved in camera placement for multi-faceted data acquisition (e.g., simultaneous speed and license plate capture).

This research aims to address these gaps by developing an AI-based transportation monitoring system tailored for the Universiti Malaya campus. The significance of this research lies in its potential to provide a cost-effective, automated, and granular approach to monitoring campus traffic, which can inform sustainable transportation policies, optimize traffic flow, and crucially, enable data-driven estimations of vehicular carbon emissions. This will support Universiti Malaya's commitment to environmental sustainability and smart campus initiatives.

The primary objectives of this early experimental study are to:

i. Establish a robust methodology for collecting diverse campus video footage.
ii. Develop an AI pipeline for vehicle detection, tracking, and license plate recognition.
iii. Integrate speed estimation for emission analysis.
iv. Identify practical deployment challenges to guide future improvements.

2. Methodology

Our methodology for developing an AI-based transportation monitoring system involved a systematic approach to data acquisition, system architecture design, and experimental implementation. The overarching goal was to collect rich video data and process it to extract critical vehicle-centric information. Figure 1 below shows the flowchart of the AI-based transportation monitoring system methodology, showing the data collection pipeline, computer vision processing architecture, and emission modeling approach.

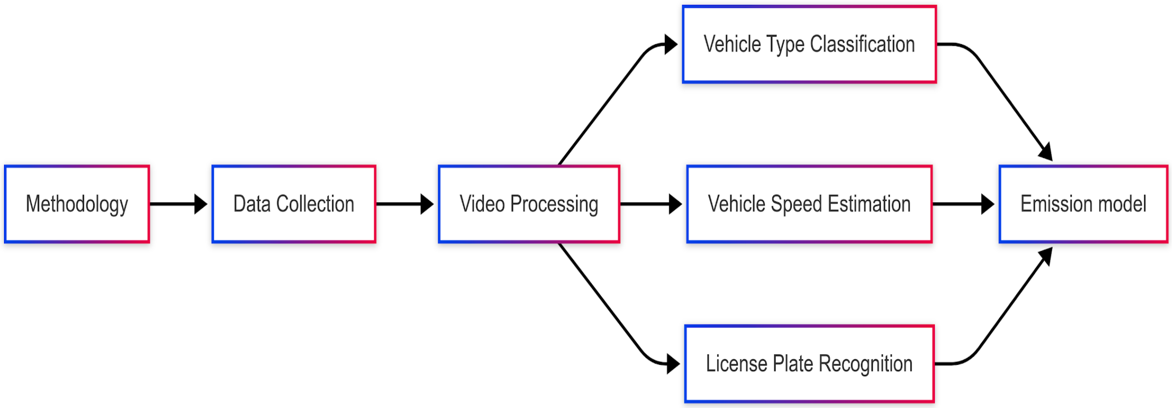

Fig. 1. Flowchart of the AI-based transportation monitoring system methodology, showing the data collection pipeline, computer vision processing architecture, and emission modeling approach

2.1 Data Collection and Camera Setup

Camera Specifications: A VIGI C540V (4MP Outdoor Full-Color Dual-Lens Varifocal Pan-Tilt Network Camera) was selected for video capture. Although intended for fixed installations, its pan-tilt and varifocal capabilities allowed flexible positioning when mounted on a tripod, enabling adaptability during the experimental phase.

Data Collection Sites: Video footage was collected from six strategically selected locations within the Universiti Malaya campus to capture varied traffic conditions and perspectives:

i. Roadside in front of the Department of Civil Engineering.
ii. Entrance area of the UM Central Library.
iii. Conjunction road after the Central Library.
iv. Roadside beside Dewan Tunku Canselor.
v. Roadside near the Physics Department.
vi. Roadside adjacent to the UM site field.

Dataset Description: From the total recorded footage, seven representative video samples were curated, covering a range of vehicle types, motion dynamics, and environmental conditions. These samples, totaling approximately 1 GB, served as the experimental dataset for testing the vehicle detection, tracking, and analysis pipeline.

2.2 System Architecture and Implementation

The processing pipeline of the AI-based transportation monitoring system was designed to extract vehicle-specific data from raw video footage, including type classification, tracking, license plate recognition, and speed estimation. The architecture integrates deep learning models with efficient video preprocessing components, all executed in a GPU-accelerated cloud-based environment.

2.2.1 Software environment and key technologies

The system was developed in Python within a GPU-enabled environment using Google Colab, facilitating rapid experimentation and model inference. Key open-source libraries and frameworks included:

i. Ultralytics YOLOv8 for vehicle detection and tracking, chosen for its real-time performance and accuracy in object detection tasks.
ii. EasyOCR for license plate text recognition, providing reliable optical character recognition on localized plate images.
iii. OpenCV for video frame processing, visualization, and pre/post-processing operations.
iv. PyTorch as the underlying deep learning framework powering YOLOv8 [19] model inference.

2.2.2 Object detection models

Two YOLO-based models were employed in the detection pipelines:

i. Vehicle Detection Model: A pre-trained YOLOv8-nano model, trained on the Common Objects in Context (COCO) dataset [20], was adapted to detect four classes of vehicles: cars, motorcycles, buses, and trucks. This model provided the foundational object-level data necessary for tracking and traffic profiling.
ii. License Plate Detection Model: A custom-trained YOLO model was incorporated to accurately localize license plates within detected vehicle regions. This model was trained on a curated license plate dataset, enabling targeted extraction of plate areas for subsequent OCR processing.

2.2.3 Optical Character Recognition (OCR) initialization

To extract text from localized license plate regions, the system employed the EasyOCR library, an open-source optical character recognition tool optimized for multiple languages and scripts. The OCR configuration was restricted to recognize only alphanumeric characters, thereby reducing noise and enhancing accuracy. GPU acceleration was leveraged to speed up the inference process, ensuring efficient processing of video frames.

2.2.4 Vehicle tracking and data aggregation

To maintain continuity of vehicle information across frames, a robust object tracking mechanism was implemented. This component supported temporal data aggregation, enabling enhanced accuracy and interpretability of vehicle-level insights.

i. Unique Vehicle Identification: Each vehicle detected was assigned a persistent unique identifier to allow continuous tracking across frames. This tracking facilitated the monitoring of individual vehicle paths within the camera's field of view.
ii. Vehicle Data History: A history log was maintained for each tracked vehicle to ensure temporal consistency. This included the initial vehicle classification (e.g., car, bus, motorcycle) and a collection of license plate text readings over time. Multiple OCR outputs were stored

and analyzed to determine the most frequently observed plate text, thereby improving robustness against transient misreads.

iii. Speed Estimation: Speed was approximated by calculating the displacement of a vehicle's centroid across consecutive frames. This pixel-based displacement was converted to real-world velocity (in km/h) using the known video frame rate and a calibrated scaling factor. The scaling factor was determined based on the camera's perspective and a pixel-to-meter conversion ratio derived from field calibration experiments.

2.2.5 Video processing pipeline

The system processed each video frame sequentially through the following operational stages:

i. Vehicle Detection and Tracking: Each new frame was analyzed using the YOLOv8 model to detect vehicles. Detected vehicles were assigned unique tracking identifiers to maintain continuity across frames.
ii. For each tracked vehicle, the system:
    - Recorded the classified vehicle type.
    - Estimated instantaneous speed based on centroid displacement between frames.
    - Cropped the region of interest (ROI) corresponding to the vehicle's bounding box and passed it to the license plate detection model.
    - If a license plate was identified, the corresponding cropped image was forwarded to the OCR module for text extraction. Multiple OCR outputs were compared across frames, and the most frequently occurring result was assigned to the vehicle's tracking ID to improve robustness.

2.3 Data Parameters Gathered

The system was designed to collect the following parameters for each detected vehicle:

i. Vehicle Speed (km/h): A key input for emission modeling.
ii. Vehicle Type: Categorized as car, motorcycle, bus, or truck.
iii. License Plate Number: Extracted alphanumeric identifier via OCR.

2.4 Emission Modelling Approach

Instead of developing a new carbon emission model, this study adopts existing, validated equations that establish a correlation between vehicle speed and emission rates, such as those proposed by Barth *et al.,* (2008) [12] and Kabit *et al.,* (2022) [21]. While the actual emission estimations have not yet been performed, the system's design ensures that the necessary speed data, along with vehicle type, is collected to enable future application of these models. This strategy allows for a focused effort on the computer vision and tracking aspects, relying on validated scientific principles for environmental impact assessment.

3. Results and Discussion

Preliminary experiments demonstrate the foundational capabilities of the proposed AI-based transportation monitoring system utilizing campus video footage. The developed pipeline successfully performs real-time vehicle detection, tracking, classification, license plate recognition, and speed estimation.

3.1 Vehicle Detection and Tracking Performance

The YOLOv8 model demonstrated reliable performance in detecting and tracking vehicles across video frames. The system consistently assigned unique identifiers to individual vehicles, enabling the extraction of temporal features such as vehicle duration within the frame and movement trajectories. Vehicle classification into four categories: car, motorcycle, bus, and truck - provided initial insight into campus traffic composition and vehicle distribution patterns.

3.2 License Plate Recognition and Speed Estimation

The system combined a custom-trained license plate detection model with the EasyOCR engine to extract alphanumeric license plate data from detected vehicles. While the accuracy of text recognition was occasionally affected by environmental conditions such as lighting, viewing angle, and plate quality, the system achieved correct extraction in many cases. To enhance reliability, multiple OCR results for each vehicle were aggregated over successive frames, and the most consistently observed result was selected as the final output.

Preliminary speed estimations were derived by tracking the centroid displacement of vehicles across consecutive frames. These displacements were converted into approximate speeds (in km/h) using the known frame rate and a calibrated pixel-to-distance scale factor. Although these estimates have not yet been quantitatively validated against ground-truth measurements, visual inspection indicated reasonable alignment with the actual movement of vehicles.

3.3 Data for Emission Modelling

The reliable acquisition of vehicle speed and classification data represents a critical foundation for the application of carbon emission estimation models. These parameters correspond directly to the input variables required by established emission equations. Although full emission calculations were not conducted during this phase, the system demonstrates the capability to generate the necessary inputs, validating its potential for future data-driven environmental impact assessments within campus environments.

4. Challenges Encountered

Several practical and technical challenges emerged during the initial experimental phase, influencing both data quality and overall system performance:

i. Camera Resolution: Early experiments were constrained by limited camera resolution, which adversely affected the accuracy of object detection and, more critically, the clarity required for license plate recognition, where fine visual detail is essential.
ii. Camera Placement Trade-offs: Determining optimal camera positioning involved balancing conflicting requirements for different system components:
    - Higher placement provided a broader field of view, facilitating more consistent vehicle tracking and improved speed estimation due to greater visible displacement. However, this often reduced the visibility of license plates, diminishing OCR accuracy.

- Lower placement enhanced license plate readability and OCR success but limited the camera's coverage area and reduced perspective cues necessary for accurate speed measurement.

These trade-offs suggest the need for a hybrid or multi-camera approach in future deployments.

i. Deployment Logistics: On-site installation presented several difficulties:
    - Mounting constraints: Securing the handheld camera to poles or other fixed structures in various campus locations was time-consuming and inconsistent.
    - Environmental conditions: High ambient temperatures during daytime recording sessions in Malaysia created operational strain, potentially leading to equipment overheating and increased physical discomfort for personnel.

5. Future Work

The early experiments have laid a solid foundation for the AI-based transportation monitoring system. However, several areas require further investigation and development to enhance its robustness, accuracy, and practical utility:

i. Optimize Models for Edge Device Deployment: The current setup utilizes a GPU in a cloud environment. Future efforts will focus on optimizing the YOLO and OCR models for deployment on edge devices (e.g., NVIDIA Jetson, Raspberry Pi with accelerators) to enable real-time, on-site processing with lower power consumption and latency. This includes model quantization and pruning.
ii. Expand to Real-time, Multi-camera System: The ultimate goal is a comprehensive, real-time monitoring system. This involves integrating multiple camera feeds, which will require solving challenges related to camera synchronization, vehicle re-identification across different camera views, and seamless data fusion.
iii. Enhance OCR Under Challenging Conditions: Improving the robustness of license plate recognition under varying lighting, weather conditions (e.g., rain, glare), and extreme viewing angles is crucial. This may involve training the OCR model on a more diverse dataset or implementing pre-processing techniques to enhance image quality.
iv. Investigate Multi-camera Fusion for Better Tracking: For complex traffic scenarios, fusing data from multiple cameras can provide a more complete and accurate understanding of vehicle movement, reduce occlusions, and improve tracking continuity compared to single-camera approaches.
v. Validation of Accuracy Metrics: A critical next step is to rigorously validate the system's accuracy, specifically quantifying precision, recall, and F1-score for vehicle detection, tracking ID consistency, license plate recognition accuracy, and most importantly, the accuracy of speed estimation against ground truth data.
vi. Carbon Emission Estimation and Analysis: With refined speed data, the next phase will involve systematically applying the chosen emission models to estimate carbon emissions for different vehicle types and traffic conditions observed on campus. This will involve analyzing trends and providing actionable insights for campus sustainability initiatives.

6. Conclusions

This paper presented early experimental endeavors towards establishing an AI-based transportation monitoring system at Universiti Malaya, leveraging campus video footage. We successfully demonstrated the feasibility of an integrated pipeline capable of vehicle detection and tracking, type classification, license plate recognition, and preliminary speed estimation. These capabilities are fundamental for our long-term objective of estimating vehicular carbon emissions on campus.

While challenges related to camera resolution, optimal placement, and deployment logistics were identified and provide valuable lessons, the preliminary results are promising. This work establishes a robust foundation for future research, including refining speed estimation, optimizing for edge deployment, expanding to multi-camera systems, and rigorously validating the system's accuracy. Ultimately, this research aims to contribute to more intelligent and sustainable transportation management within the Universiti Malaya campus and serve as a model for similar urban environments, providing data-driven insights for environmental monitoring and planning.

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