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RESEARCH ARTICLE

A Cyber-Physical System Based on On-Board Diagnosis (OBD-II) for Smart City

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Abstract

This paper proposes designing and structuring a Cyber-Physical System (CPS) with a specific focus on vehicles equipped with on-board diagnosis (OBD-II). The purpose of the CPS is to collect and assess data pertaining to the vehicle's Electronic Control Unit (ECU), such as engine RPM, speed, and other relevant parameters. The OBD-II scanner utilizes the obtained data on mass airflow (MAF) and vehicle speed to compute CO_2 gas emissions and fuel consumption. The data is wirelessly communicated using a GSM module to a Semantic Web. The CPS also uses GPS tracking to ascertain the vehicle's whereabouts. A Semantic Web is utilized to construct a database management system that stores and manages sent data. A graphical user interface (GUI) is created to facilitate data analysis. It undergoes a sequence of performance tests to verify the system's functionality. The results demonstrate that the system can accurately read parameters, process data, transfer information, and display readings.

Keywords: automobiles, intelligent vehicle, microcontroller, Cyber-Physical System, embedded System.

1 Introduction

Cyber-physical systems (CPS) have recently become increasingly popular and have drawn the attention of researchers, engineers, and entrepreneurs. One particularly interesting use is vehicle monitoring. Research on real-time vehicle monitoring systems and driver behavior analysis has increased significantly in recent years [1].

The online monitoring systems provide access to various data, including diagnostic data, speed, engine RPM, position, and measurements from many engine sensors [2, 3]. A remote vehicle health monitoring system enables vehicle owners to protect themselves and their vehicles by providing access to historical and current diagnostic data. Automatic problem detection and reporting to automotive specialists is a key feature of this system [4]. The cloud-based architecture of this system facilitates the ability to access data remotely using cell phones or PCs. The engine and power

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transmission can be inspected during the vehicle's operation in a different location.

On-board diagnosis (OBD-II) devices [5] gather engine parameters and GPS data and communicate them to other microcontroller-based devices and a cloud server. Cloud server as a platform to enable real-time data transmission and processing for an IoT-based automobile monitoring system [6], supporting the visualization of vehicle status information such as location and sensor data.

A microcomputer known as Raspberry Pi runs on the open-source Linux operating system, and has been widely reviewed for its robotic and embedded applications [7]. Raspberry Pi 4B, introduced in 2019, features an integrated Wi-Fi module for wireless internet access. Several advantages of Raspberry Pi can be identified when comparing it with other microcontrollers like Arduino [8]. IoT-based approaches using RFID, GSM, and GPS modules have been proposed for real-time bus tracking and safety monitoring [9]. However, such systems typically lack implementation specifics and do not incorporate OBD-II interfaces. The use of a Raspberry Pi with an OBD-II tool in a vehicle's diagnostic system is described in [10]. The system has a Bluetooth dongle for communicating with other Bluetooth devices, but it cannot upload data to a remote server for monitoring.

Pan et al. [11] explored a driving behavior model using OBD-II data, demonstrating how parameters such as speed and RPM can be wirelessly transmitted and visualized to support driver behavior analysis.

The work in [12] utilizes an OBD-II interface and a Raspberry Pi for vehicle monitoring, enabling real-time diagnostics acquisition, processing, and command transmission to the vehicle. However, the article lacks detailed implementation specifics regarding the Raspberry Pi configuration and online data visualization. A more comprehensive description of these aspects is needed, as it would be valuable for practicing engineers and researchers interested in practical deployments. The key goals of our research are as follows:

1. A cost-effective CPS has been developed to monitor a vehicle's electronic control unit (ECU) data.
2. GPS coordinates complement the ECU data within the system to facilitate data analytics.
3. Creating an intelligent transportation systems-related Semantic Web platform involves integrating advanced technologies to facilitate smart mobility.
4. This platform aims to optimize transportation networks, enhance safety, and improve overall efficiency through data-driven insights and real-time monitoring.

The article's structure continues: Section 2 presents the related work, while Section 3 details the module methodology. Section 4 presents the results and analysis related to it. Finally, Section 5 concludes this work with future directions.

2 Related Work

Various OBD-II logging devices are available, some of which are included in Table 1. For our research, we needed a low-cost device that fulfilled all the requirements in the table. The most affordable devices were the Arduino platform and the Bluetooth scanner. Many new projects have emerged in OBD-II loggers in the last few years.

A low-cost fleet monitoring prototype model was developed [13]. The model involves attaching sensors and ECUs to each vehicle in the fleet to collect various parameters and location details. The communication between the vehicles' CAN-bus and the Raspberry PI 3 is achieved using PICAN2. The connection between PICAN2 and a vehicle's OBD-II is established through OBD-II cables. To obtain location details, the prototype utilizes the Adafruit Ultimate GPS module. Through a cellular network, the Hologram Nova makes

Table 1. Comparison of existing OBD loggers and the proposed CPS.

Technology	Stand-Alone	GSM-Capable	Config-urable	GPS	Data Recorder	CAN
OBD-II Scanner (Bluetooth)	×	✓	✓	✓	✓	×
OBD-II Scanners	✓	×	×	×	×	✓
OBD Mini Logger [20]	✓	×	×	✓	✓	×
Car Chip Pro [21]	✓	×	×	✓	✓	×
CarTwin Data Logger [22]	×	✓	×	×	✓	✓
DashDyno SPD ProPack	✓	×	×	×	✓	✓
IOSiX OBD-II Datalogger	✓	×	×	×	✓	×
Proposed CPS	✓	✓	✓	✓	✓	✓

communicating easier for the Raspberry PI and the server. The fleet management data is visualized through a web application. The Python programming language collects fleet data, and Raspbian OS is the platform. The database is MongoDB, and Node.js is utilized to operate the fleet management service.

Cumin et al. [14] examined the use of OBD-II diagnostic tools for proactive maintenance of automobiles and motorcycles, integrating statistical techniques with CAN-bus diagnostic signals to support vehicle health monitoring. The European OBD-II standard monitors many aspects of fuel and air intake. This includes metrics such as fuel injection pressure, intake air temperature, ignition advance, intake air quality, and exhaust settings for control, like lambda sensors. The analysis incorporates various standard operational data inputs, such as vehicle speed, engine RPM, oil condition, and coolant temperature. The system also monitors various aspects such as braking, safety, transmission, brake pads, brake fluid, spark plug conditions, active chassis, and motor oil quality. These parameters are key characteristics of the proposed system.

Several methods have been proposed to measure and minimize pollution, with the transportation sector accounting for 29% of GHG emissions. An approach that uses machine learning techniques and the OBD-II data from the vehicle to estimate pollution levels was proposed [15]. They observed that vehicle RPM and speed were positively correlated with CO_2 emissions. Their study concluded that the driving pattern impacts GHG emissions.

For fleet management and driver behavior analysis, Türk and Challenger [16] designed an Internet of Things-based solution. This system collects sensor data, including fuel consumption, speed, brake use, RPM, and steering angle, by connecting to the vehicle's onboard diagnostics interface. The data and the driver's details are uploaded to a server for future analysis. The system also includes analysis software to analyze driver behavior and vehicle status thoroughly. The authors in [17] proposed an intelligent and integrated automatic fault diagnosis system, which enables proactive vehicle maintenance to help prevent accidents.

Baghli et al. [18] developed a data acquisition and tracking system for monitoring vehicle energy consumption and performance, enabling remote vehicle monitoring useful for fleet management applications. The mobile app receives an accident alert with location information if the vibration sensor detects an impact above a predefined threshold. Nugroho et al. [19] developed an IoT-based Car Data Recorder to monitor vehicles and report accidents. They suggested the parts for the system as an Arduino Mega 2560, an HC-05 Bluetooth module, an accelerometer, an ELM327 OBD-II reader, and a GSM module SIM800L. An alert is transmitted via SMS whenever an impact with a magnitude above 4G is detected. Smith and Miller [23] proposed an OBD-II data logger design optimized for large-scale deployments, addressing challenges in data storage and communication for fleet monitoring applications. Ramai et al. [24] presented a low-cost OBD-II data-logging framework for battery electric vehicles, providing a scalable architecture for vehicle parameter monitoring.

The primary difference between this paper's solution and those previously discussed is that our proposal utilizes a bottom-up strategy. Our research focuses on developing a universal and cost-effective platform to collect data from a vehicle's interior and exterior. Because of its open and scalable architecture, intelligent transport services can be implemented on this platform.

3 Methodology

The proposed system utilizes OBD-II technology and the Semantic Web to provide a low-cost, real-time CPS. Vehicle owners can access historical and real-time vehicle data through the Semantic Web. The system allows users to view real-time charts displaying OBD parameter variations and provides live location tracking on a Google map. Furthermore, a Semantic Web maintains trip-related information, including fuel consumption, CO_2 emissions, and duration. The system can notify users of problems and maintenance needs via the cloud server.

3.1 OBD Scanner and On-Board Diagnostics

Since 1996, automobile manufacturers have initiated the integration of electronic sensors into automobiles, commonly referred to as the ECU. The primary objective was to monitor car sensors to increase fuel efficiency and decrease pollution. OBD was an additional advantage of ECU that enabled the diagnosis and logging of vehicle data for technical evaluation. OBD and ECU are connected via DLC, and PID codes capture data from vehicle sensors. Interoperability problems emerged in OBD's early days since no universal standard had been established. The

OBD-II standard interface was suggested to solve this issue, and software implementations for OBD-II-based engine diagnostics have since been developed [25]. The industry has now adopted several protocols as standards, with the main difference being the placement of communication pins, such as ISO 9141-2, ISO 14230 KWP2000, ISO 15765 CAN, SAE J1850 PWM, and SAE J1850 VPW. The sensor data for this study is collected by connecting the sensor node to the test vehicle's ECU using the ELM327 OBD-II scanner. The sensor node and the ELM327 scanner are connected via the HC-05 Bluetooth module, as seen in Figure 1.

3.2 Sensor node

The Arduino Uno ATmega328P is the compute board for the sensor node shown in Figure 1. This microcontroller is based on the AVR architecture and operates at 16MHz. It has 32 KB of flash memory and offers 14 digital and six analog I/O pins for connecting sensors and peripherals [26]. The sensor node integrates a Bluetooth HC-05 module to facilitate connection with the ELM327 OBD-II scanner. Using this module, a wireless connection can be established between the sensor node and the OBD-II scanner. The parameters of vehicle sensors are gathered by the OBD-II scanner ELM327 at 12-sec intervals. These parameters include coolant temperature, RPM, speed, and MAF (Mass Air Flow) of the vehicle. The data from these sensors is essential for determining the vehicle's fuel efficiency and CO_2 emissions, as explained in Section 3.3.

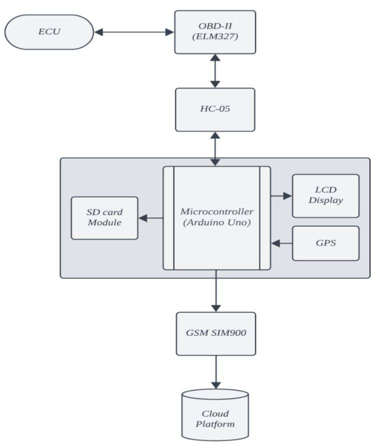

Figure 1. Block diagram of Cyber-Physical systems.

Integrating a GPS module (NEO-6M) enables the vehicle's sensor data to be geo-referenced to the road network, providing essential information such as GPS coordinates and timestamps. These GPS-based references and timestamps are critical in evaluating numerous trip variables such as fuel consumption, journey time, and CO_2 emissions with precise locations.

The sensor node incorporates a GSM module that transmits the measured parameters (RPM, speed, MAF, etc.) to ThingSpeak, a free and open-source Semantic Web. The values are transmitted to the Semantic Web and stored on an SD card module, as shown in Figure 1. In the case of a communication interruption and unavailability of Wi-Fi access, this local logging is executed to ensure data integrity.

3.3 Implementation and Algorithm

The proposed method is implemented in C++ within the Arduino IDE and executed on an ATmega328P-based Arduino Uno. Figure 2 shows the program flow of the software for the CPS implemented in the vehicle.

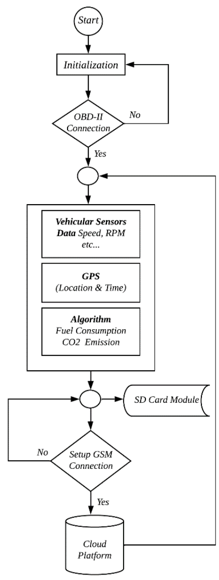

Figure 2. The Cyber-Physical system flowchart for vehicles.

The DLC connector allows the sensor node to interact with the ELM327 OBD-II scanner while driving. This connection is established using Bluetooth. After establishing a connection, the sensor node initiates regular data retrieval from a range of vehicle sensors, such as RPM, speed, and MAF, at intervals of 12 sec. These sensor readings are then used to calculate the fuel consumption and CO_2 emissions for the entire trip.

In the next stage, the integrated sensors detect and gather data from the sensed parameters, as shown in Figure 2. This data includes GPS coordinates and time, which are utilized to determine the geographical location, speed, fuel consumption, and CO_2 emissions for various segments of the road network. The third step involves executing algorithms to estimate fuel usage and CO_2 emissions, as detailed in Sections 3.4 and 3.5. The processed data is transmitted to the cloud platform (Thingspeak) using a GSM module. However, as shown in Figure 2, the data is also stored locally on an SD card module to limit the possibility of GSM connectivity interruptions. The duration of programmed execution is 15 sec. This results in four data sets uploaded to the cloud service (ThingSpeak) per minute.

3.4 Consumption of fuel instantly

Fuel consumption can be expressed as miles per gallon (MPG) or liters per km (l/km), the fuel used per travel unit. Various factors, including traffic conditions, vehicle type, driver conduct, and time of day, might affect fuel use. Instantaneous fuel consumption can be calculated using Eq.(1) [28]. Machine learning approaches have also been proposed to estimate fuel consumption from OBD data with higher accuracy [27]. However, it is important to note that this calculation relies on the availability of the vehicle's Fuel Flow parameter (PID 0x5E).

The instantaneous fuel consumption C (in $\frac{l}{km}$) can be calculated as the ratio of the fuel flow F (in $\frac{l}{h}$) to the vehicle speed V (in $\frac{km}{h}$). Thus, the fuel consumption is equal to the ratio of the fuel flow to the vehicle speed, as shown in the following formula:

$$C = \frac{F}{V} \tag{1}$$

However, the Fuel Flow parameter is not available in most vehicles. This could be due to a fuel flow sensor not being there or the manufacturer choosing not to include one between the fuel tank and the engine carburetor. Furthermore, the fuel flow parameter is unavailable on the test vehicle used to validate this research. In this case, Eq. (2) can be used to figure out the Fuel Flow. Fuel Flow can be calculated using the Air-to-Fuel ratio (AFR) (PID 0x44) and Mass Air Flow (MAF) (PID 0x10), as shown in Eq. (2).

$$\text{Fuel Flow}\left(\frac{l}{h}\right) = \frac{\text{MAF}}{\text{AFR} \times \text{FD}} \times 3600 \tag{2}$$

FD stands for fuel density, equivalent to 820 grams of petrol per cubic decimeter.

3.5 Emissions of Carbon Dioxide

The carbon and oxygen atomic masses can be utilized to calculate the amount of CO_2 created during the combustion of fuel containing carbon. The atomic masses of oxygen and carbon are 16 and 12, respectively. Therefore, the formula for CO_2 may be determined by adding the atomic masses of carbon and two oxygen atoms, resulting in a total of 44. Using this equation, we can calculate the estimated amount of CO_2 created after burning one kilogram of carbon content.

$$\frac{44}{12} \approx 3.67\,\text{kg of}\,CO_2 \tag{3}$$

The system uses the mass air flow sensor's values and the vehicle's speed data to determine the amount of CO_2 emissions. The OBD-II interface is used to read this data. The mass air flow sensor monitors how much air enters the engine's intake.The amount of petrol utilized in gallons per hour (GPH) can be calculated using the value acquired from the MAF sensor. The fuel consumption can subsequently be converted to liters per hour (LPH). Finally, the fuel efficiency in terms of km per liter(KPL) can be determined.

$$\text{GPH} = \text{Mass Air Flow} \times 0.0805 \left(\frac{g}{h}\right) \tag{4}$$

$$\text{LPH} = \text{GPH} \times 3.785 \left(\frac{l}{h}\right) \tag{5}$$

$$\text{KPL} = \frac{\text{Speed}}{\text{LPH}} \left(\frac{km}{l}\right) \tag{6}$$

Depending on the fuel type utilized, different fuels have different amounts of CO_2 emissions per liter. A diesel engine's CO_2 emissions per liter are 2.6 kilograms, compared to 2.3 kilograms in a gasoline engine.

3.6 Semantic Web

ThingSpeak is a free and open-source Semantic Web for processing, storing, and visualizing data. It provides data visualization capabilities without programming and includes integrated MATLAB analytics functionality [29]. Built-in APIs in ThingSpeak allow data to be received and stored from HTTP-based sensor nodes. Moreover, it is capable of using the logged data for data analytics.

4 Results and Analysis

Tests were conducted using a CPS, as shown in Figure 3. The proposed approach was evaluated and tested in a 2013 Toyota passo with an automated gearbox and a

1000CC engine. The driving route through urban areas 5 km is shown in Figure 4. The software on the laptop manages communication with the OBD-II Link device. It was created using Arduino IDE C++, especially for this research study. Multiple parameters, RPM, vehicle speed, and other essential parameters, were monitored and recorded throughout the designated route. Figure 5 shows the test program used to collect these results.

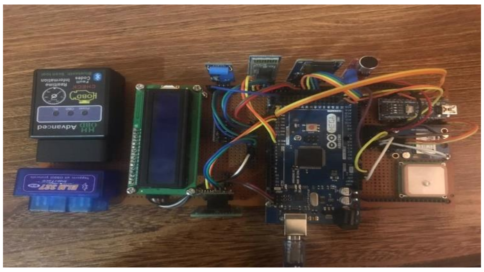

Figure 3. Overview of the proposed prototype.

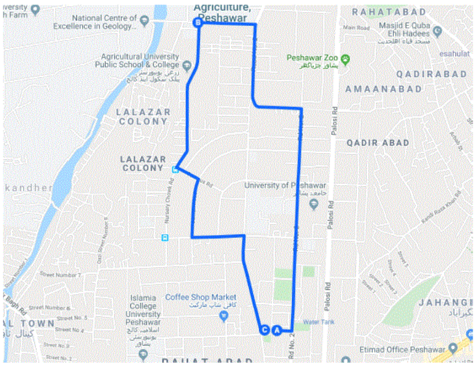

Figure 4. Route of Travel.

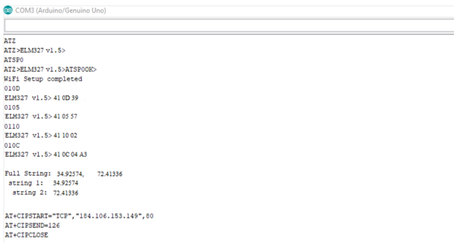

Figure 5. A snapshot of the test program.

The capability and performance of the CPS to measure various vehicle parameters, such as RPM, speed, and others, are depicted in Figures 6-15. The figure analysis shows that the maximum speed that could be obtained was approximately 60 km per hour. The maximum fuel consumption that could be seen was 0.866 liters per 100 km, as shown in Figure 6. It is important to note that fuel consumption increased at lower speeds. Furthermore, Figure 7 shows that the maximum CO_2 emission per 100 km was 4.99 kilograms, and the maximum observed speed was 60 km/h. Interestingly, lower speeds were also linked to increased CO_2 emissions.

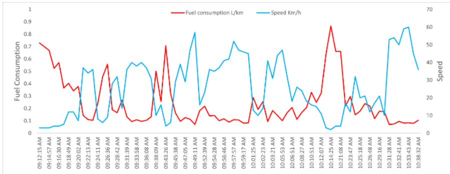

Figure 6. Fuel consumption and speed.

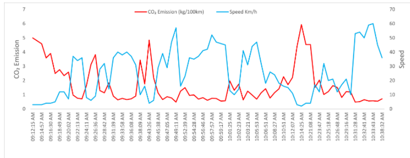

Figure 7. Carbon dioxide (CO_2) Emission and Speed.

Furthermore, the graphical representation of all supported OBD-II parameters is presented with the parameters above, as illustrated in Figures 6-12. At the time of data acquisition, the speed is 15 km/h, as shown in Figure 9, and the engine RPM is 1027, as shown in Figure 13. A temperature of 95 degrees Celsius is also documented for the engine coolant.

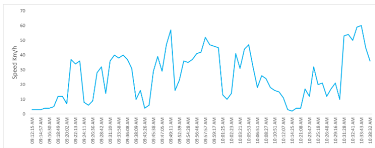

Figure 8. Speed of the Vehicle.

Figure 9. Speed during Test.

The MAF sensor measures the mass flow rate of air entering the engine. This measurement is essential for determining the ideal spark timing and how much fuel to supply. The MAF value in the OBD-II system is given in g/sec and varies depending on the engine model and capacity. Figure 10 shows the MAF values and time stored in a database.

RPM is a measurement of how many times the crankshaft of an engine spins in one minute. This parameter is essential for drivers because it helps

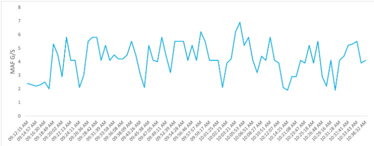

Figure 10. MAF of Vehicle.

Figure 11. MAF during Test.

them figure out when to transfer gears for maximum fuel efficiency, especially when operating a car with a manual transmission. If the RPM exceeds the vehicle's speed, the engine is idling, which wastes fuel. In vehicles with manual gearboxes, fuel consumption might vary based on driver behavior. The RPM values recorded during the test drive in the Semantic Web are shown in Figure 12.

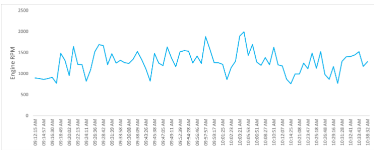

Figure 12. Engine RPM of Vehicle.

Figure 13. Engine RPM during the Test.

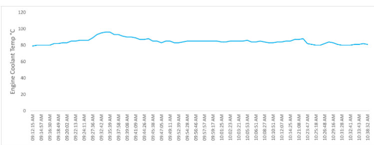

Figure 14. Coolant Temperature of Vehicle.

Figure 15. Coolant temperature during Test.

A vehicle's coolant temperature is a crucial sensor that shows the engine's temperature. Monitoring it is critical since a greater coolant temperature usually signals a higher engine temperature. The CPS periodically uses the PID 05 to retrieve the coolant temperature. The figure below illustrates the continuous monitoring of the values retrieved by the CPS.

5 Conclusion

Testing the OBD-II reader's communication with the Semantic Web confirmed that the system could retrieve sensor readings from an OBD-II compliant vehicle. Tests on a real vehicle showed that the system could measure RPM, speed, coolant temperature, etc. The approach minimizes costs by integrating technologies by eliminating the need to buy many devices with distinct functions. The design also incorporates the capability to measure metrics like fuel consumption, CO_2 emission, and GPS tracking that are not typically available with standard OBD-II interfaces. The system powered off when the car's engine was turned off, which disabled wireless connectivity and GPS location tracking.

Future work could focus on improving battery backup systems that keep essential functions running even when the vehicle's motors are turned off. This would enable GPS location tracking and continuous wireless connection. To increase overall efficiency, it's also necessary to decrease the delay brought on by system initializations. Due to the current delay in preserving crucial initial parameter measurements, the automobile cannot be driven until all initializations are finished. To reduce this delay, new approaches must be investigated and developed.

Data Availability Statement

Data will be made available on request.

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This work was supported without any funding.

Conflicts of Interest

Inam Ullah served as an Associate Editor of *ICCK Transactions on Intelligent Systematics* at the time of manuscript submission. To ensure the integrity of the peer-review process, Inam Ullah was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. Syed Haider Ali is affiliated with the Pakistan Council of Scientific & Industrial Research, Peshawar, Pakistan. The authors declare that this affiliation had no influence on the study design, data collection, analysis, interpretation, or the decision to publish, and that no other competing interests exist.

Ethical Approval and Consent to Participate

This study involved vehicle testing conducted on public roads using a privately owned 2013 Toyota Passo. The driving tests were performed by a member of the research team who provided informed consent for data collection. The data collected, including GPS trajectory, vehicle speed, and engine parameters, were used solely for research purposes and stored securely with access restricted to the research team. No personally identifiable information beyond anonymized vehicle performance metrics was retained in the final dataset. The GPS location data collected during testing was processed in accordance with applicable data protection regulations. As this study did not involve clinical interventions, medical procedures, or third-party human subjects, formal ethics committee approval was not required under the applicable institutional guidelines. Nevertheless, all procedures were conducted in compliance with local traffic regulations and with due regard for public safety.

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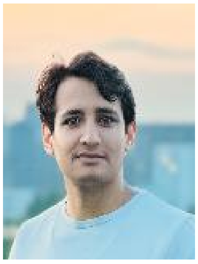

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