Scientific Paper / Artículo Científico

UNIVERSIDAD POLITÉCNICA SALESIANA ECUADOR
INGENIUS
Revista de Ciencia y Tecnología
https://doi.org/10.17163/ings.n32.2024.01
pISSN: 1390-650X / eISSN: 1390-860X

IoT Architecture for Vehicle Pollutant Gas Emission Monitoring and Validation through Machine Learning

Arquitectura de IoT para el monitoreo de emisiones de gases contaminantes de vehículos y su validación a través de Machine Learning

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Received: 16-11-2023, Received after review: 12-12-2023, Accepted: 16-02-2024, Published: 01-07-2024

Abstract

This study proposes an IoT architecture for monitoring vehicle pollutant gas emissions in response to increasing concerns about air pollution and global warming. The architecture is based on a node equipped with DHT22, MQ9, and MQ135 sensors to capture temperature, humidity, and gas emissions. This node effectively communicates through the LTE network to send the data to the ThingSpeak platform. An analysis of CO_2, CO, and CH_4 pollution levels is conducted using the collected data. This data is validated through the technical review of a test vehicle. Subsequently, an Artificial Neural Network (ANN) is trained using a specific database of CO_2 emissions from cars in Canada. As a result, a high coefficient of determination (R^2) of 99.2 % is achieved, along with low values of Root Mean Square Error (RMSE) and Mean Squared Error (MSE), indicating that the model makes accurate predictions and fits well with the training data. The ANN aims to predict CO_2 emissions and verify CO_2 data from the IoT network. The architecture demonstrates its capability for real-time monitoring and its potential to contribute to pollution reduction.

Keywords: Vehicle pollution, pollutant gases, IoT, LTE, sensors.

Resumen

Este estudio propone una arquitectura IoT para el monitoreo de emisiones de gases contaminantes en vehículos, en respuesta a la creciente preocupación por la contaminación del aire y el calentamiento global. La arquitectura se basa en un nodo equipado con sensores DHT22, MQ9 y MQ135 para capturar la temperatura, humedad y emisiones de gases, mismo que se comunica de manera efectiva a través de la red LTE para enviar los datos a la plataforma *ThingSpeak*. Se lleva a cabo un análisis de los niveles de contaminación de CO_2, CO y CH_4 mediante los datos recopilados. Estos datos se validan mediante la revisión técnica de un vehículo de prueba. Posterior, se entrena una red neuronal artificial (ANN) utilizando una base de datos específica de emisiones de CO_2 de vehículos en Canadá, como resultado se obtiene un R^2 alto de 99,2 % y los valores de RMSE y MSE bajos, esto indican que el modelo está haciendo predicciones precisas y se ajusta bien a los datos de entrenamiento. La ANN tiene como objetivo predecir las emisiones de CO_2 y verificar los datos de CO_2 provenientes de la red IoT. La arquitectura demuestra su capacidad para el monitoreo en tiempo real y su potencial para contribuir a la reducción de la contaminación.

Palabras clave: contaminación vehicular, gases contaminantes, IoT, LTE, sensores

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Suggested citation: Torres Guin, W.; Sánchez Aquino, J. ; Bustos Gaibor, S.; Coronel Suárez, M. “IoT Architecture for Vehicle Pollutant Gas Emission Monitoring and Validation through Machine Learning,” *Ingenius, Revista de Ciencia y Tecnología*, N.° 32, pp. 9-17, 2024, DOI: https://doi.org/10.17163/ings.n32.2024.01.

1. Introduction

Accelerated urbanization and increased demand for transportation have exacerbated the environmental issues associated with road transport [1]. Despite a temporary reduction in emissions during 2020 due to the COVID-19 pandemic, global warming continues, accompanied by rising atmospheric pollution [2]. The challenges posed by climate change are global, transcending national borders. Emissions of greenhouse gases such as methane (CH_4), hydrofluorocarbons (HFCs), and carbon dioxide (CO_2) disrupt the balance between the Earth and its atmosphere. Specifically, CO_2 emissions, releasing approximately eight billion tons annually from the combustion of fossil fuels in transportation, heating, and energy production, have become a critical factor in worsening global warming [3]. These emissions primarily originate from industrial and vehicular sources, with passenger cars accounting for 75% of the carbon dioxide emissions [4].

Heavy vehicles, including buses and trucks are responsible for approximately 25% of road emissions. This contribution could increase unless appropriate measures are implemented. Despite stricter regulations to enhance fuel efficiency and reduce greenhouse gas emissions, the number of vehicles on the road has significantly increased. This surge has led to a marked rise in the kilometers these vehicles travel, further exacerbating their impact on atmospheric pollution [5].

Monitoring pollution in the vehicular sector is crucial for several reasons [6, 7]. It provides vital data on the sources and intensity of air pollution across public, private, and freight transportation environments. This information is essential for developing policies and strategies to reduce exposure and enhance air quality. Furthermore, such surveillance helps identify practical approaches to address this problem, including the implementation of cleaner fuels and the adoption of advanced technologies. These measures play a critical role in fostering sustainable solutions and promoting healthier urban environments for travelers and the population in general.

The challenge in vehicular transportation arises from the lack of precise and reliable air quality data. This deficiency drives the need to design and test a mobile measurement system capable of addressing these gaps [8]. The capture, processing, and analysis of pollution data in urban transportation are crucial. These processes improve the understanding of air pollution sources and subsequently encourage the development of targeted policies and interventions to address this issue.

Below, we review various IoT proposals for emission monitoring. Senthilkumar et al. [9] describe an integrated system where sensors collect air quality data and transmit it to fog nodes. Moses [10] proposes a cloud-based scheme to monitor air quality using sensors that measure pollutant levels such as NO_x, CO, O_3, PM10, PM2.5, and SO_2, along with environmental data like humidity and temperature. The collected data is updated in the cloud via a LoRa Gateway infrastructure and LoRa nodes. Time series analysis, support vector regression models, and multilayer perceptron neural networks are used to predict pollutant concentrations. Behal and Singh [11] use the ANFIS method to predict air quality based on pollutant levels and a modified air quality index (m-AQI). A support vector regression model is employed to forecast values, which involves determining a best-fit line that is robust to outliers.

Shetty et al. [12] apply IoT methods to monitor vehicular emission rates and use real-world data on a global scale to forecast carbon monoxide levels. Wei et al. [13] utilize vehicular monitoring to provide owners with details about current pollution levels at their location and their vehicles emission rates, using machine learning techniques to predict pollution based on historical and current data collected by sensors. Mumtaz et al. [14] offer a solution that combines advanced IoT sensors with machine learning capabilities to monitor and predict indoor air quality, thus enabling the measurement of various pollutants. In Mohamed's study [15], an IoT sensor network is employed to detect eight types of pollutants through machine learning techniques, achieving a high accuracy rate of 99.1% in classifying indoor air quality.

Therefore, in a world increasingly aware of the importance of sustainability and reducing environmental pollution, monitoring vehicular emissions has become a critical challenge. The rapid urbanization and expansion of the vehicle fleet have intensified the urgent need to control and mitigate air pollution to preserve environmental quality and safeguard public health. In this context, the Internet of Things (IoT) emerges as a powerful tool that enables real-time data collection and analysis, thus allowing the efficient and effective monitoring and management of vehicular emissions.

This project focuses on developing an IoT architecture for monitoring vehicular emissions of polluting gases, supported by machine learning techniques. This architecture will enable the real-time collection of accurate data on emissions from operating vehicles, along with subsequent analysis and validation of this data using machine learning algorithms. The implementation of this proposal is critically important for several reasons.

- **Emission Control:** Real-time monitoring of vehicle emissions enables identifying and proactively managing pollution sources, which is crucial for achieving air quality objectives and reducing environmental impact.
- **Technology and Sustainability:** The combination of IoT and Machine Learning constitutes an

advanced technological approach that enhances sustainability and illustrates how innovation can drive positive change in society.

2. Materials and Methods

The proposed architecture and its constituent elements for constructing the sensor node for gas acquisition in a test vehicle, specifically a 2012 Kia Sportage, are presented in the following section.

2.1. Proposed IoT Architecture

In this Internet of Things (IoT) architecture (see Figure 1), a complete system is designed to monitor vehicle emissions of polluting gases, referencing the proposals in [16, 17]. The architecture comprises several layers that work together to collect, store, and validate emission data.

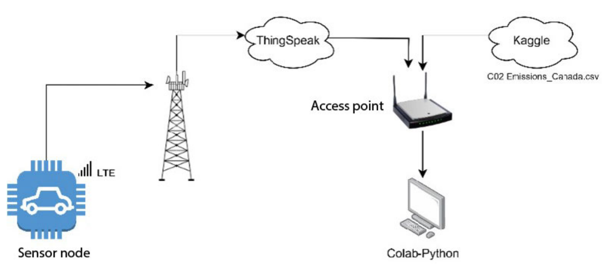

Figure 1. IoT Architecture for Pollutant Gas Monitoring.

Below, the architecture is described considering its layers and functionality:

- **Perception Layer:** In the perception layer, a node equipped with a DHT22 temperature sensor along with MQ-135 and MQ-9 gas sensors, is utilized for gas detection. This node captures real-time temperature, humidity, and air pollutant concentration data.
- **Network Layer:** The network or communication layer is essential for transmitting the data captured by the sensor node. The LTE network has been selected as the communication medium, offering reliable connectivity, wide coverage for the sensor node, and potential network scalability.
- **Application Layer:** In the application layer, the IoT platform ThingSpeak has been integrated to store and manage the data collected by the sensors. ThingSpeak provides a user-friendly interface and enables secure data storage via the HTTP protocol, thus facilitating subsequent access and analysis.
- **Data Analysis:** Once the data has been uploaded to ThingSpeak, a more detailed analysis is conducted to verify the distribution of carbon dioxide (CO_2), carbon monoxide (CO), and methane (CH_4) emission data. Colab, a Python programming collaboration platform, is utilized for this purpose.
- **Data Validation:** A comprehensive verification process is conducted to ensure the accuracy of the data captured by the sensors, including tests based on the technical inspection of a test vehicle. Additionally, regression analysis is performed using a Canadian-origin CO_2 emissions database as a reference point to verify the data received from the IoT platform. This procedure facilitates comparison, validation, and prediction.

2.2. Design of the Sensor Node

The sensor node design (Figure 2) incorporates the LILYGO® TTGO T-Call V1.4 controller, which features a variety of essential functionalities. This device provides LTE network connectivity via a SIM800L module and leverages the ESP32 for wireless capabilities, including Wi-Fi and Bluetooth. Additionally, the sensor node includes a built-in GPS positioning system, enabling precise geolocation of measurements. The sensors, carefully chosen for their accuracy, include the DHT22 sensor for measuring environmental temperature and humidity. Meanwhile, the MQ135 and MQ9 sensors detect concentrations of CO, CO_2, and methane (CH_4). It should be noted that the DHT22 sensor is connected to a digital port on the controller, whereas the MQ135 and MQ9 sensors are connected to analog ports, offering a versatile interface for data acquisition. This comprehensive configuration allows for precise measurement and collection of critical data necessary for monitoring vehicular pollutant gas emissions.

The DHT22 sensor operates within a voltage range of 3.3–5 VDC and can measure relative air humidity from 0 to 99% RH with an accuracy of ±2% (at 25°C) and a resolution of up to 0.1%. It measures temperature within a range of -40°C to 80°C, with an accuracy of ±0.5°C and a resolution of 0.1°C. The sensor refreshes at a rate of 1 Hz (reporting every 1 second) and employs the Wire protocol for its operation. Its functionality is supported by the DHT.h library.

The MQ-135 sensor operates through a specific detection mechanism involving gas interactions, which result in variations in its electrical resistance. Although the sensor does not inherently discriminate between gases, it can be calibrated and configured to detect specific gases based on their unique response patterns. By precisely adjusting the sensor parameters and applying advanced signal processing techniques, it becomes possible to distinguish between various gases and their concentrations, thereby enabling effective differentiation between gases such as CO and CO_2. According to the technical information provided by the sensor, the load resistance is 20.1 $k\Omega$, and the resistance in clean air conditions is 10 $k\Omega$. Considering this data, Figure 3 illustrates the sensor calibration curve along with the model equation, where Ro is defined as the constant representing the sensor resistance in response to a concentration of 0.4 mg/L, and Rs denotes the sensor resistance in another context.

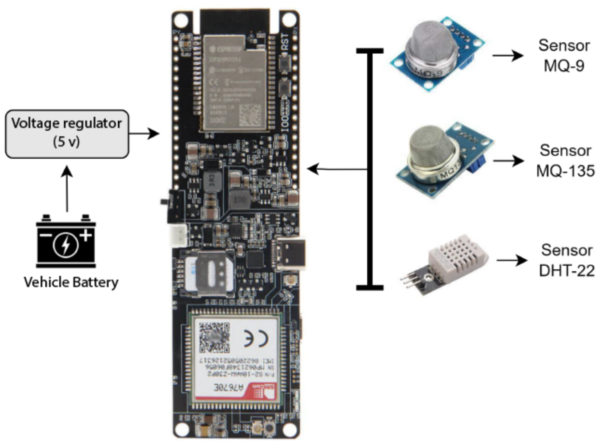

Figure 2. IoT Sensor Node.

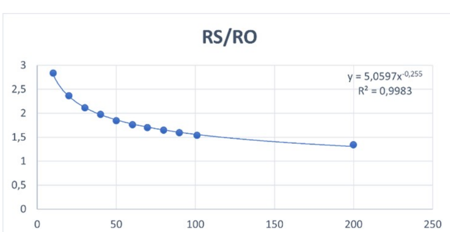

Figure 3. Calibration Curve of the MQ-135 Sensor.

The MQ-9 sensor was used to determine methane concentration (CH_4). The sensor's analog output data is transmitted to the controller's analog input. The conversion of this data by the analog-to-digital converter (ADC) occurs within a range of 0 to 3.3 V. The characteristics and specifications, such as load and resistance in fresh air, are similar to those of the MQ-135, as both sensors originate from the same manufacturer and share identical values. Consequently, the same configurations are utilized.

2.3. Implementation of the Sensor Node into the Vehicle

The IoT sensor node is positioned following the indications provided in Figure 4, allowing for strategic placement of the sensors directly at the vehicle's exhaust pipe outlet. The controller in contrast, is securely installed inside the car, establishing a direct connection with the onboard computer. This connection facilitates real-time visualization of the data captured by the sensor. Moreover, the sensor is connected to the ThingSpeak platform via LTE technology, utilizing the HTTP protocol for efficient data transmission and storage. This comprehensive design allows for effective monitoring of vehicle pollutant gas emissions, thereby providing valuable real-time information. For power supply, the device is connected to the vehicle's battery.

In Figure 5, the physical sensor node installed in the vehicle is depicted for sample collection.

In Figure 6, the placement of sensors on the vehicle's exhaust pipe is visible.

It is essential to highlight that GPS is used to visualize the precise position of the vehicle and obtain a detailed record of its path.

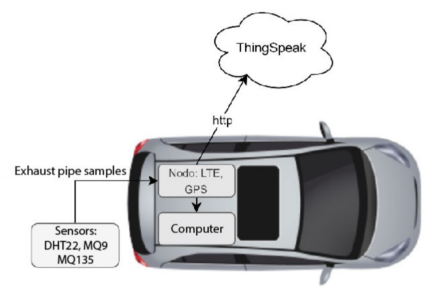

Figure 4. Arrangement of the IoT Sensor Node in the Vehicle.

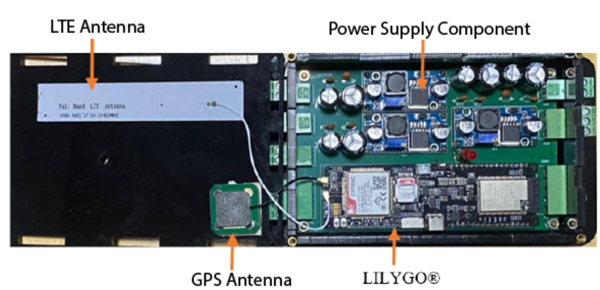

Figure 5. IoT Sensor Node Installed.

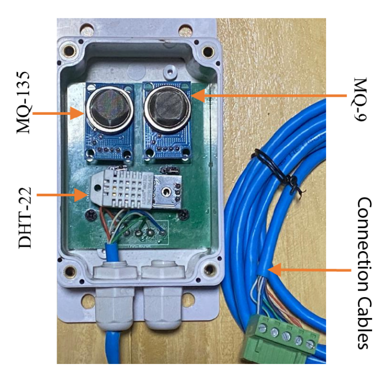

Figure 6. Sensors for Data Collection.

3. Results and Discussion

Firstly, the results obtained from the 50 samples collected from the exhaust pipe with the engine idling and undergoing specific changes in revolutions, are presented to illustrate the variability in data collection. These samples reveal the levels of pollutants, specifically CH_4 (methane), CO_2, and CO. The data from sensors, expressed in parts per million (ppm), provide detailed insight into the emissions.

Upon analysis, it is observed that the concentration of CH_4 (see Figure 7) varies approximately between 45 and 65 ppm, reflecting the data distribution. Additionally, Figure 8 highlights that CO oscillations range from 26,000 to 38,000 ppm, while CO_2 levels fluctuate between 121,000 and 140,000 ppm.

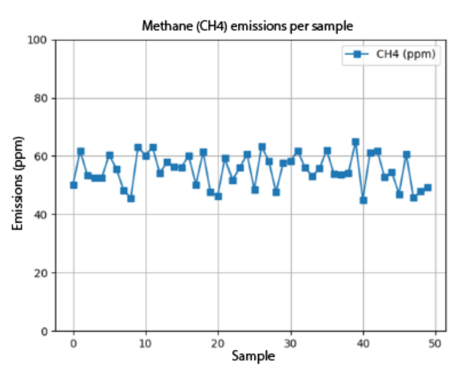

Figure 7. Graph of the data for CH_4.

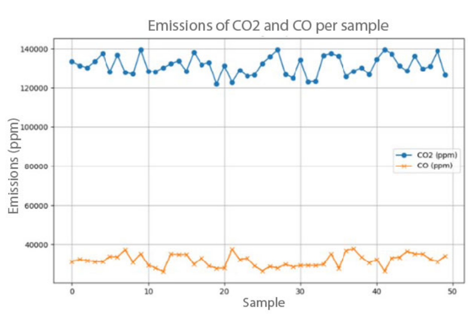

Figure 8. Graph of the data for CO and CO_2.

It is rworth noting that these values fall within the specified ranges, as mentioned in the study [17]. These findings emphasize the importance of closely monitoring vehicle emissions to gain a clear understanding of engine pollutant variability. Importantly, the samples are collected approximately every 3 to 4 minutes, reflecting the time required for the controller to process and upload the data to the ThingSpeak platform.

The graphical representation of temperature and humidity data was not performed because these parameters do not vary abruptly according to the sensor position in the exhaust pipe. During measurements, the temperature displayed minimal oscillations, consistently ranging from approximately 30 to 37°C. Simultaneously, humidity exhibited a similar stability, fluctuating between 80% and 99%.

The data capture validation was performed through a comprehensive technical inspection of a 2012 Kia Sportage SUV used as the test vehicle. This evaluation yielded CO2 concentrations ranging from 12% to 14%, with the engine idling and CO concentrations ranging from 2.6% to 3.8%. According to Segura [18], this information can be utilized to estimate emissions in ppm, assigning CO_2 an estimated maximum level of 140,000 ppm and CO a maximum of 38,000 ppm.

This information supports the reliability of the collected data, as the vehicle technical inspection as the results from the vehicle technical inspection are consistent with the measurements obtained by the sensors. The precise calibration of the sensors for capturing these gases improves the accuracy of the estimations, thereby confirming that the concentration of CH_4 is also accurate and reliable.

To evaluate the vehicle's pollution level, focusing on CO_2 as a crucial reference variable due to its significant contribution to vehicle emissions, a conversion is performed to calculate the units in grams of pollution per kilometer traveled (g/km). The importance of this data is underscored by its verification against the vehicle's technical specifications, which specify a pollution level of 158 g/km of CO_2 in urban environments.

Therefore, to calculate the amount of carbon dioxide (CO_2) released per kilometer traveled, if the vehicle exhibits a CO_2 concentration of 14%, this percentage indicates that 14% of the gas volume in the vehicle's exhaust pipe consists of CO_2. The remaining 86% comprises other types of exhaust gases, such as nitrogen, oxygen, and unburned hydrocarbons (HC), among others.

To accurately calculate the amount of CO_2 emitted, several factors must be considered, including the vehicle's efficiency, the volume of fuel consumed, and the amount of CO_2 generated per liter of fuel burned.

Vehicle efficiency: This parameter is derived from the vehicle's technical specifications, which indicate a fuel consumption rate of 5.7 liters per 100 kilometers.

Amount of CO_2 per liter of fuel: The amount of CO_2 produced by burning one liter of gasoline varies depending on the fuel's exact composition. In this case, it amounts to approximately 2.8 kg of CO_2 per liter of gasoline. Using these parameters, we then apply the following equation (1) to calculate the CO_2 emissions in g/km.

$$\begin{aligned} CO_2\left(\tfrac{g}{km}\right) &= C_{l/km} * CO_{2kg/l} * 100_{g/kg} \\ CO_2\left(\tfrac{g}{km}\right) &= 0.057_{l/km} * 2,8_{\frac{kg}{l}} * 100_{\frac{g}{kg}} \\ &= \mathit{159{,}6\ g/km} \end{aligned} \tag{1}$$

This calculation provides a close approximation to the vehicle's technical specifications, which estimate CO_2 emissions at 158 g/km.

With this established conversion data, an Artificial Neural Network (ANN) model is developed to predict potential emissions of pollutant gases in the automotive fleet. For this purpose, a dataset from Kaggle [19] that contains information on vehicle pollutant gas emissions in Canada is utilized. This dataset was selected because it includes information about the vehicle used in our sensor tests. Consequently, a learning model is tailored to our specific scenario, enabling the prediction of CO_2 pollution levels.

The database includes essential parameters such as make, model, vehicle class, engine size, number of cylinders, transmission type, fuel type, fuel consumption in the city (L/100 km), fuel consumption on highways (L/100 km), as well as CO_2 emissions measured in grams per kilometer (g/km). During the analysis, correlations between these parameters and CO_2 emissions are evaluated to identify the variables that have the most significant relationships. Variables demonstrating notable correlations are selected for training the Artificial Neural Network (ANN) model, thereby focusing the model on the features that most significantly influence CO_2 emissions and improving its predictive capability.

This correlation is illustrated in Figure 9, which shows that the variables engine size, number of cylinders, fuel consumption in the city, and fuel consumption on highways exert the most significant influence on CO_2 emissions.

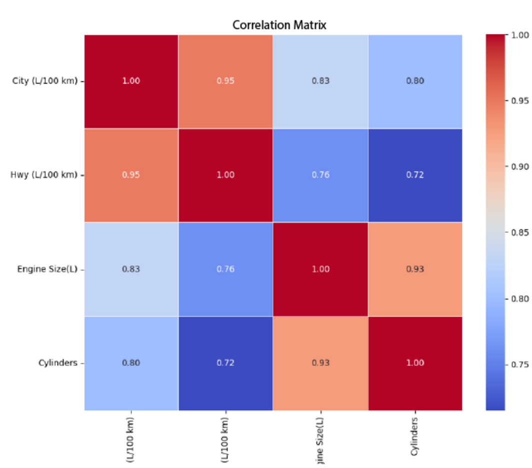

Figure 9. Correlation of Variables Influencing CO_2 Emissions.

Progress is made in developing a machine learning model using an Artificial Neural Network (ANN) based on the information obtained from the correlation analysis. This model is configured using the TensorFlow library in Python, as outlined in the following structure (see Figure 10).

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                6464
_________________________________________________________________
dense_1 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_2 (Dense)              (None, 16)                528
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 17
=================================================================
Total params: 9,089
Trainable params: 9,089
Non-trainable params: 0
_________________________________________________________________
```

Figure 10. Structure of the ANN.

The model structure is defined as sequential, indicating a neural network architecture where the layers are arranged in sequence. It comprises four densely connected layers (Dense), labeled $dense_1$, $dense_2$, and $dense_3$. The first layer contains 64 neurons, the second 32, the third 16, and the output layer includes a single neuron. Each layer utilizes the 'relu' (Rectified Linear Unit) activation function, except for the output layer, which employs the 'linear' activation function suitable for CO_2 emissions. The parameters are automatically calculated and detailed in Figure 10, which displays the number of trainable parameters and the total sum of parameters, amounting to 9,089. These parameters represent the weights and biases of the neural network that are adjusted during the training process to optimize the model's performance.

Following the model training, Figure 11 illustrates the model's loss over the training sessions. It shows that as the epochs progress, there is a predictable decrease in loss and an increase in accuracy, suggesting that the model is successfully learning and improving its ability to make accurate predictions. Therefore, Figure 11 confirms that the model is appropriately trained.

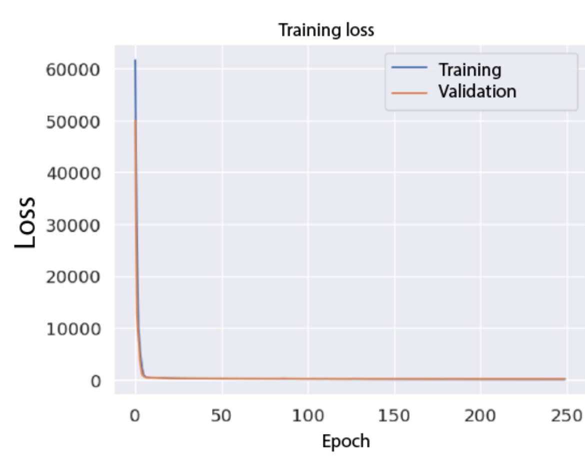

Figure 11. Loss During Training.

Then, to assess the performance of a machine learning model in its predictions, it is essential to measure its accuracy. It is achieved through the use of performance metrics such as the root mean square error

(RMSE), the mean square error (MSE), and the coefficient of determination (R squared). These metrics help confirm the accuracy of regression models [19] and play a crucial role in evaluating and refining learning models, enabling a deeper understanding of their ability to explain and predict data. These metrics are presented below in equation (2):

To assess the predictive performance of a machine learning model, it is crucial to measure its accuracy. This is accomplished by employing performance metrics such as the root mean square error (RMSE), the mean square error (MSE), and the coefficient of determination (R-squared). These metrics are instrumental in verifying the accuracy of regression models [19] and play an essential role in evaluating and refining learning models. They enable a deeper understanding of the models' capabilities to explain and predict data. These metrics are presented below in Equation (2):

$$
\begin{gathered}
MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_{real}^{(i)} - y_{pred}^{(i)}\right)^2 \\
RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{real}^{(i)} - y_{pred}^{(i)}\right)^2} \\
R^2 = 1 - \frac{SS_{res}}{SS_{tot}}
\end{gathered} \tag{2}
$$

Where SS_{res} is the sum of the squares of the discrepancies between the observed and predicted values. SS_{tot} represents the sum of the squares of the differences between the observed values and and their mean. An R^2 value close to 1 indicates a good fit of the model, whereas a value close to 0 suggests that the model does not adequately explain the data's variability.

The results of the model metrics are auspicious: the coefficient of determination (R^2) reaches an outstanding 0.992, indicating an exceptional ability to explain the variability in the data. The mean squared error (MSE) is at 20.59, demonstrating a reasonably low average magnitude of squared errors, meanwhile, the root mean squared error (RMSE) stands at 4.53, confirming significant accuracy in the model's predictions. These results underscore the model's robust capability to forecast emissions of pollutant gases in the automotive fleet, affirming its suitability for predictive applications. These values are illustrated in Figure 12.

Coefficient of determination (R^2): 0.9922332006414919
Mean Squared Error (MSE) : 20.59925370801521
Root Mean Squared Error (RMSE): 4.538640072534416

Figure 12. Results of the model metrics.

To evaluate the effectiveness of the developed model, a test comparing the actual values of pollutant gas emissions with the predictions generated by the neural network was conducted (Figure 13). This visual analysis sought the proximity of the points to an ideal diagonal line, representing perfect prediction. The dispersion and distribution of points on the graph facilitate a quick assessment of the model's ability to capture variability in the actual data. Alignment close to the diagonal indicates precise predictions, while significant dispersion suggests areas for improvement in the model's predictive accuracy. This approach provides an intuitive and visual assessment of the quality of the model's predictions relative to the actual data.

Therefore, implementing an Artificial Neural Network (ANN) to monitor vehicle pollutant gas emissions significantly enhances and effectively complements conventional monitoring methods. Unlike simpler, linear approaches, ANNs can capture complex nonlinear relationships in the data, thereby offering improved prediction accuracy. They dynamically adapt to changes, providing more robust and flexible monitoring. Furthermore, ANNs efficiently process multidimensional and complex data, simultaneously handling multiple inputs such as temperature, humidity, and various gas emissions. The potential for machine learning and continuous improvement enables ongoing enhancements in accuracy as more data on vehicle emissions are collected.

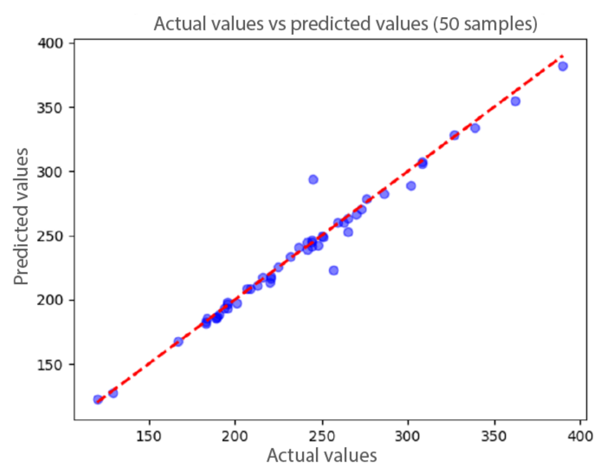

Figure 13. Model Testing.

4. Conclusions

This article thoroughly examines the monitoring of pollutant gas emissions in vehicles, from the construction of a dedicated sensor node for data collection to the development of an Artificial Neural Network (ANN) model for predicting CO_2 emissions. The implementation of the sensor node, equipped with DHT22, MQ9, and MQ135 sensors, has proven effective in capturing critical data such as temperature, humidity, and gas concentrations during tests on a 2012 Kia Sportage SUV. The validation of these data, conducted through a technical vehicle review, confirms the accuracy and reliability of the measurements.

Subsequently, an ANN model was utilized, leveraging vehicle emissions data from Canada and focusing on key variables identified through correlation analysis. The model results, boasting a remarkable coefficient of determination (R^2) of 99.2%, underscore its ability to predict CO_2 emissions accurately. These findings demonstrate the effectiveness of integrating advanced sensor technologies with machine learning models, providing a robust approach for monitoring and predicting vehicle emissions, thereby contributing to the management and mitigation of environmental pollution.

For future work, the proposed architecture will be implemented in urban buses, where the Artificial Neural Network (ANN) is expected to significantly enhance air quality control and vehicle condition monitoring. This implementation will facilitate more effective management of circulation policies and planning.

References

[1] J. Krause, C. Thiel, D. Tsokolis, Z. Samaras, C. Rota, A. Ward, P. Prenninger, T. Coosemans, S. Neugebauer, and W. Verhoeve, "EU road vehicle energy consumption and CO_2 emissions by 2050 – Expert-based scenarios," *Energy Policy*, vol. 138, p. 111224, 2020. [Online]. Available: https://doi.org/10.1016/j.enpol.2019.111224

[2] M. M. Ajmal, M. Khan, M. K. Shad, H. AlKatheeri, and F. Jabeen, "Empirical examination of societal, financial and technology-related challenges amid COVID-19 in service supply chains: evidence from emerging market," *The International Journal of Logistics Management*, vol. 34, no. 4, pp. 994–1019, Jan 2023. [Online]. Available: https://doi.org/10.1108/IJLM-04-2021-0220

[3] J. Lynn and N. Peeva, "Communications in the IPCC's Sixth Assessment Report cycle," *Climatic Change*, vol. 169, no. 1, p. 18, Nov 2021. [Online]. Available: https://doi.org/10.1007/s10584-021-03233-7

[4] Z. Yang and A. Bandivadekar, *Light-duty vehicle greenhouse gas and fuel economy standards*. The International Council on clean Transportation, 2017. [Online]. Available: https://bit.ly/4anzh8u

[5] R. Guensler, "Data needs for evolving motor vehicle emission modeling approaches," *The University of California, Transportation Center*, 1993. [Online]. Available: https://bit.ly/3THURO5

[6] Y. Lu, *Traffic-Related PM2. 5 Air Pollution and Schools in Proximity to Major Roadways in Shanghai, China*. University of Washington, Department of Urban Design and Planning, 2016. [Online]. Available: https://bit.ly/43KjOgq

[7] N. Kozarev and N. Ilieva, "Plume rise in particular meteorological conditions," *Journal of the University of Chemical Technology and Metallurgy*, vol. 46, pp. 305–308, 01 2011. [Online]. Available: https://bit.ly/3VLqMQ3

[8] N. Barmparesos, V. D. Assimakopoulos, M. N. Assimakopoulos, and E. Tsairidi, "Particulate matter levels and comfort conditions in the trains and platforms of the Athens underground metro," *AIMS Environmental Science*, vol. 3, no. 2, pp. 199–219, 2016. [Online]. Available: https://doi.org/10.3934/environsci.2016.2.199

[9] R. Senthilkumar, P. Venkatakrishnan, and N. Balaji, "Intelligent based novel embedded system based IoT enabled air pollution monitoring system," *Microprocessors and Microsystems*, vol. 77, p. 103172, 2020. [Online]. Available: https://doi.org/10.1016/j.micpro.2020.103172

[10] L. Moses, Tamilselvan, Raju, and Karthikeyan, "IoT enabled Environmental Air Pollution Monitoring and Rerouting system using Machine learning algorithms," *IOP Conference Series: Materials Science and Engineering*, vol. 955, no. 1, p. 012005, nov 2020. [Online]. Available: https://dx.doi.org/10.1088/1757-899X/955/1/012005

[11] V. Behal and R. Singh, "Personalised healthcare model for monitoring and prediction of airpollution: machine learning approach," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 33, no. 3, pp. 425–449, 2021. [Online]. Available: https://doi.org/10.1080/0952813X.2020.1744197

[12] C. Shetty, B. Sowmya, S. Seema, and K. Srinivasa, "Chapter eight - air pollution control model using machine learning and IoT techniques," in *The Digital Twin Paradigm for Smarter Systems and Environments: The Industry Use Cases*, ser. Advances in Computers, P. Raj and P. Evangeline, Eds. Elsevier, 2020, vol. 117, no. 1, pp. 187–218. [Online]. Available: https://doi.org/10.1016/bs.adcom.2019.10.006

[13] "Guest Editorial: Special Section on Integration of Big Data and Artificial Intelligence for Internet of Things," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 4, pp. 2562–2565, 2020. [Online]. Available: https://doi.org/10.1109/TII.2019.2958638

[14] R. Mumtaz, S. M. H. Zaidi, M. Z. Shakir, U. Shafi, M. M. Malik, A. Haque, S. Mumtaz, and S. A. R. Zaidi, "Internet of Things (IoT) Based Indoor Air Quality Sensing and Predictive

Analytic—A COVID-19 Perspective," *Electronics*, vol. 10, no. 2, 2021. [Online]. Available: https://doi.org/10.3390/electronics10020184

[15] M. Abdel-Basset, G. Manogaran, M. Mohamed, and E. Rushdy, "Internet of things in smart education environment: Supportive framework in the decision-making process," *Concurrency and Computation: Practice and Experience*, vol. 31, no. 10, p. e4515, 2019. [Online]. Available: https://doi.org/10.1002/cpe.4515

[16] M. Montaño Blacio, J. González-Escarabay, O. Jiménez-Sarango, L. Mingo-Morocho, and C. Carrión-Aguirre, "Design and deployment of an IoT-based monitoring system for hydroponic crops," *Ingenius. Revista de Ciencia y Tecnología*, no. 30, pp. 9–18, 2023. [Online]. Available: https://doi.org/10.17163/ings.n30.2023.01

[17] M. Montaño Blacio, V. García Santos, D. Jaramillo Chamba, W. Torres Guin, and L. Chuquimarca Jiménez, "Empowering Low-Power Wide-Area Networks: Unlocking the Potential of Sigfox in Local Transmission," in *Advanced Research in Technologies, Information, Innovation and Sustainability*, T. Guarda, F. Portela, and J. M. Diaz-Nafria, Eds. Cham: Springer Nature Switzerland, 2024, pp. 417–429. [Online]. Available: https://doi.org/10.1007/978-3-031-48930-3_32

[18] J. K. Segura Gómez, *Prototipo de un sistema IoT para medición de gases de efecto invernadero.* Universidad Santo Tomás. Colombia, 2021. [Online]. Available: https://bit.ly/3J4OvDl

[19] Kaggle. (2020) CO_2 Emission by Vehicles. Kaggle. [Online]. Available: https://bit.ly/3J7Navw