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Monitoring and improving CO_2 concentration in classroom based on AIoT technology

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Abstract

The paper presents the monitoring and improvement of CO_2 concentration in the classroom through an AIoT system including Raspberry Pi 3 connected to the MH - Z19B CO_2 gas sensor, DHT11 temperature - humidity sensor and Raspberry Pi camera. The collected data including temperature, humidity, current CO_2 gas and the number of people in a 70 m^2 classroom are continuously sent to ThingSpeak for analysis and forecasting CO_2 concentration in the classroom using the Multi-Layer Perceptron (MLP) model and linear regression model (LR). The forecasted CO_2 gas concentration results help to give early warnings and control the fan system in the classroom when the predicted CO_2 concentration is greater than 1000 ppm to maintain safe air quality in the classroom, improve concentration and health of learners. The system was tested in real classroom conditions, showing 95.77% accuracy with LR and 98.21% with MLP in predicting CO_2 concentration. This research contributes to improving classroom air quality, contributing to protecting health and improving students' learning efficiency.

Keywords: AIoT, LR, MLP, predicted CO_2 concentration, ThingSpeak.

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1. Introduction

According to health organizations such as OSHA and WHO, when CO_2 concentration is above 1000 ppm, it begins to affect health, causing fatigue, headaches and reducing the ability to concentrate of learners. However, most classrooms in schools today are not equipped with CO_2 concentration monitoring systems. Applying AIoT technology to monitor and improve CO_2 concentration is a necessary solution to improve the learning environment of students.

Pandiaraj Kadarkarai et al. studied an IoT-based system for real-time air quality monitoring, integrated with an automatic air filtration mechanism [1]. The system includes an ESP8266 connected to a DHT11 sensor and an MQ135 sensor to collect temperature, humidity and CO_2 data for processing, transmitting data to a cloud platform and displaying it on LCD. The results show that the system operates continuously, automatically filtering the air when the air quality decreases.

Kanika Seth et al. applied IoT technology to monitor the air quality of an office building [2]. Data such as temperature, humidity, CO_2 concentration and fine dust (PM) were collected in real time, monitored and adjusted the air filtration system accordingly. This study helps to significantly improve the air quality in the building with a clear reduction in CO_2 and PM concentrations.

This paper proposes solutions based on the combination of AI models (specifically LR and MLP) and IoT to monitor and improve CO_2 concentration in a 70m^2 classroom. The system is designed in three main stages: (1) Raspberry pi 3 connects MH-Z19B, DHT11 sensors and camera to Raspberry Pi 3 to collect data and send it to ThingSpeak. (2) Train and deploy LR and MLP models to predict CO_2 concentration. (3) Predict CO_2 concentration in classrooms, if CO_2 concentration is greater than 1000 ppm turn on classroom fan system to improve classroom air quality.

2. Methodology

A. System block diagram

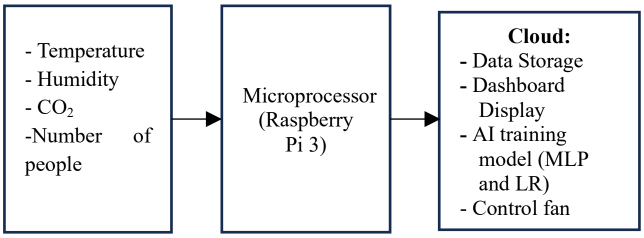

Fig 1. System block diagram

Figure 1 depicts the block diagram of a CO_2 concentration prediction system based on sensor data and AI models [3]. First, the sensors collect environmental parameters including temperature, humidity, CO_2 concentration and number of people in a $70m^2$ classroom. These data are sent to the central processor, which is responsible for pre-processing, normalizing and feeding the data into the prediction model. After the model calculates and generates a predicted CO_2 value, the results are transferred to the display block for visualization on the user interface, and the system can also issue warnings or control devices such as ventilation fans when the CO_2 concentration exceeds the threshold. Thereby, the entire system operates seamlessly from data collection, processing, prediction to control and warning.

B. Hardware connection diagram

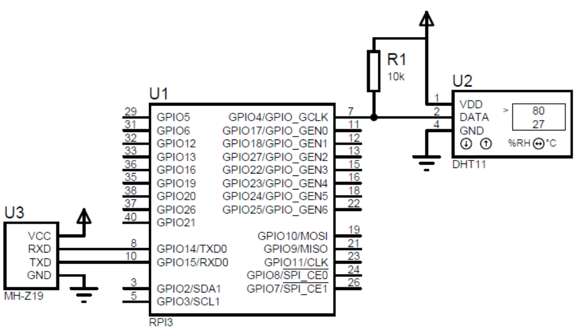

Fig 2. Connection diagram of MH-Z19B and DHT11 sensors with Raspberry Pi 3

Figures 2 show the diagram of connecting Raspberry Pi 3 with MH-Z19 sensor to measure CO_2 concentration and DHT11 sensor to measure temperature and humidity. The current temperature, humidity and CO_2 gas concentration data are sent by Raspberry Pi 3 to the cloud (ThingSpeak).

Figure 3 shows the connection of a Raspberry Pi 3 to a camera module via an FFC cable plugged into the CSI port [4]. This connection allows the Raspberry Pi 3 to collect the number of people in the classroom and this data is also sent to ThingSpeak.

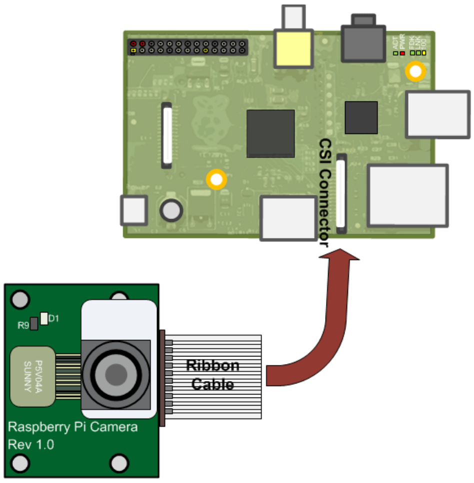

Fig 3. Connection diagram of RPi Camera with Raspberry Pi 3

C. Linear Regression (LR) Approach

The linear regression approach is represented as follows:

$$\hat{y}=w_1.\,x_1+w_2.\,x_2+w_3.\,x_3+w_4.\,x_4+b \quad (1)$$

where $\hat{y}$: predicted value; x_1: current temperature (°C); x_2: current humidity (%); x_3: current CO_2 concentration (ppm); x_4: number of people; $\mathbf{w_1}, \mathbf{w_2}, \mathbf{w_3}, \mathbf{w_4}$: weights reflecting the influence of each variable on CO_2 [5,6,7].

D. Multi-Layer Perceptron (MLP) Approach

Table 2. shows the MLP model parameter table of the experiment

Parameter	Value
Number of hidden layer neurons	32/16
Hidden layer 1 activation function	ReLU (Rectified Linear Unit)
Hidden layer 2 activation function	ReLU (Rectified Linear Unit)
Activation function at the output layer	Linear

Learning rate	0.001
Objective function	Mean Squared Error (MSE)

The research model is built on a multi-layer neural network [8, 9, 10]. The model has 4 input layer neurons including: number of people, current CO_2 gas, temperature and humidity; Hidden layer 1 consists of 16 neurons; Hidden layer 2 consists of 32 neurons and an output layer is CO_2 gas prediction.

Overall Model:

$$Y=ReLU(ReLU(x.w_1+b_1).w_2+b_2)w_3+b_3 \quad (2)$$

where $x=[x_1, x_2, x_3, x_4]$; w_1, w_2, w_3: are the weight matrices b_1, b_2, b_3: are the bias coefficients of each layer; and ReLU is the nonlinear activation function.

E. Root Mean Square Error (RMSE) and Accuracy

The Root Mean Square Error (RMSE) measures how far the predicted CO_2 concentrations are from the actual CO_2 concentrations [11,12].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{pred,i} - y_{actual,i}\right)^2} \quad (3)$$

where n = number of CO_2 samples; $y_{pred,i}$: predicted CO_2 value at sample i; $y_{actual,i}$: actual CO_2 measurement at sample i

Accuracy based on RMSE:

$$Accuracy\ \% = \left(1 - \frac{RMSE}{y_{actual}}\right) * 100\% \quad (4)$$

3. Results and discussion

Raspberry Pi 3 reads and processes data from DHT11, MHZ19B sensors and RPI camera in 70m^2 classroom, sent to ThingSpeak [13,14,15] as follows:

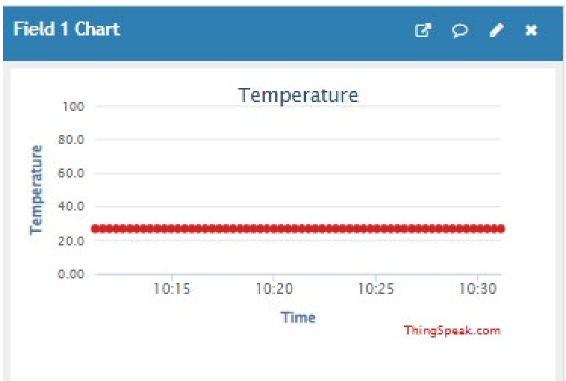

Fig 4. Temperature at the time of observation

Temperature and humidity data are collected by Raspberry Pi 3 from the DHT11 sensor and sent to ThingSpeak at the observation time in Figure 4 and 5. Temperature and humidity are almost stable throughout the measurement period, without major fluctuations.

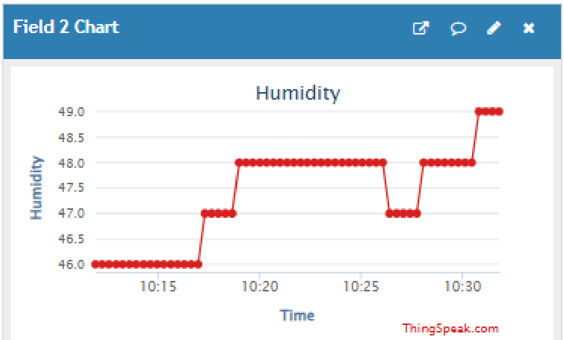

Fig 5. Humidity at the time of observation

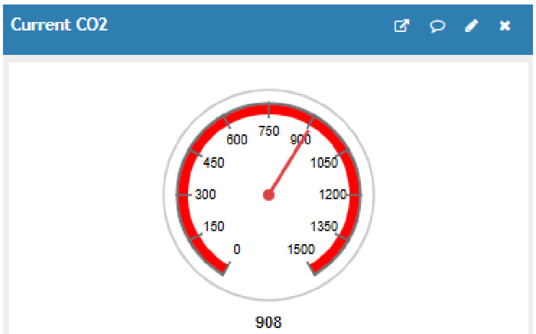

Fig 6. Current CO_2 at the time of observation

The current CO_2 gas data collected by Raspberry Pi 3 from MH-Z19B sensor is sent to ThingSpeak as shown in Figure 6. The actual measured value at the time of observation is 908 ppm, within the allowable range (<1000 ppm) according to indoor air quality standards. This shows that the air at the time of observation in the classroom is still at a safe level for health.

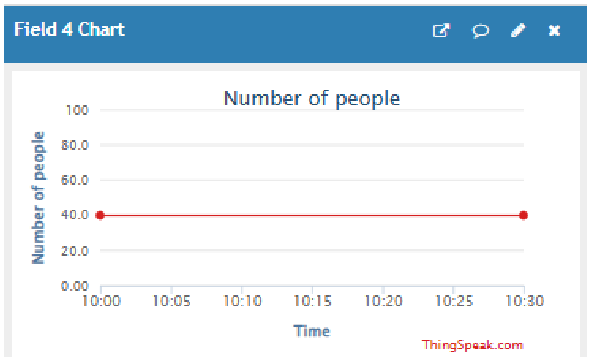

Fig 7. Number of people at the time of observation

Figure 7 shows the number of people data collected by the Raspberry pi 3 from the RPI camera and sent to ThingSpeak. At the time of observation, there were 40 students in the class.

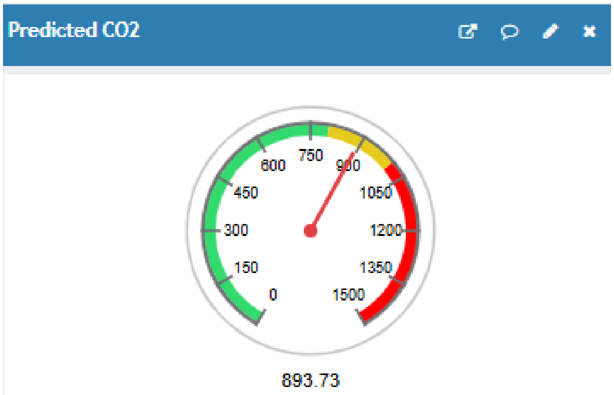

Fig 8. Predicted CO_2 concentration using RG

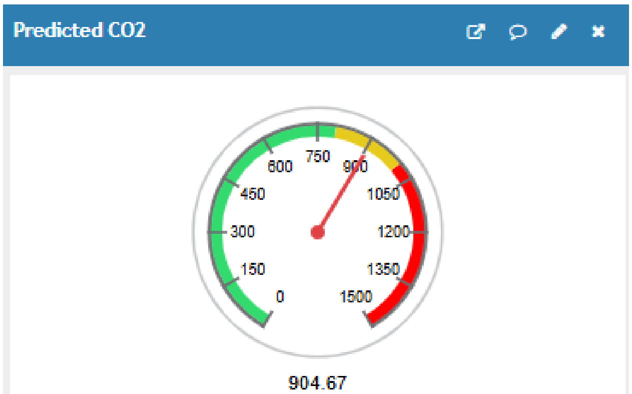

Fig 9. Predicted CO_2 concentration using MLP

Figure 8 and 9 shows the predicted result of CO_2 concentration at the observation time after training the LR model is 893.73 ppm and MLP model is 904.67 ppm (at a mild warning level). If the CO_2 concentration in the classroom exceeds 1000 ppm, the fan system in the classroom is automatically turned on to improve the CO_2 concentration in the classroom.

Table 1. Comparison of RMSE and accuracy parameters of LR and MLP

Approach	Sample number	RMSE (ppm)	Accuracy (%)
LR	3307	21.958	95.77
MLP	3307	9.317	98.21

Table 1 shows the prediction results of CO_2 gas concentration by two methods, RG and MLP [16,17,18]. The results show that the MLP method is better than the RG method in the problem of monitoring and improving the concentration of CO_2 gas in a classroom with an area of 70 m^2.

The study by Dani Yassine et al. (2024) [19] focused on assessing the impact of factors such as temperature, humidity and number of people on indoor air quality, especially CO_2 concentration. However, the two studies pursued different approaches and objectives. Dani Yassine used open data sources and applied classification models to determine CO_2 levels by group, in which Logistic Regression achieved an accuracy of 97.39%. This result shows that humidity and number of people are two factors that strongly influence CO_2 variation, thereby providing an overview direction for IAQ improvement. In contrast, the author's study aimed at the problem of predicting continuous CO_2 values in ppm using regression models such as Linear Regression and MLP. With 3307 experimental data samples, the LR model achieved an RMSE of 21,958 ppm and an accuracy of 95.77%, while the MLP model outperformed with an RMSE of only 9,317 ppm and an accuracy of 98.21%, which is higher than the results of Dani Yassine. This shows that the MLP model is more suitable for real-time CO_2 forecasting, especially in IoT systems that require high accuracy.

Compared with the study by Fatih Gül et al. (2024) [20] on the classification and comparison of air quality sensor technologies, especially CO_2 sensors, it is possible to see a clear difference in scope and objectives between the two works. Fatih Gül's study provides an overview of the operating principles, advantages and disadvantages of each type of sensor and application orientation in environmental monitoring systems. However, this work mainly stops at the theoretical analysis level, without experimental implementation with specific environmental data. In contrast, the author's study was conducted on a real IoT system with 3307 data samples measured directly from CO_2 sensors in a classroom environment. From this experimental data, the author builds and evaluates CO_2 forecasting models, including linear regression (LR) model and MLP neural network, achieving RMSE results of 21,958 ppm and 9,317 ppm, respectively, with an accuracy of up to 98.21% for the MLP model. Therefore, while Fatih Gül's research is comprehensive and sensor technology-oriented, the author's research is highly applicable, comprehensively implemented experimentally and provides clear quantitative results for practical air quality monitoring systems.

4. Conclusion

This paper shows that the application of LR method with accuracy of 95.77% and MLP with accuracy of 98.21% to predict CO_2 concentration in a 70m^2 classroom is feasible and effective. This study has demonstrated the combination of MH-Z19B sensors, DHT11 sensors, RPI cameras with Raspberry Pi 3 to collect accurate data and send to ThingSpeak. The system not only has the function of real-time monitoring but also has the function of improving CO_2 concentration in the classroom, specifically turning on the classroom fan system when the predicted CO_2 concentration is greater than 1000 ppm. This study is highly applicable, providing a comprehensive solution from collecting data from sensors, analyzing data, building predictive AI models to making smart decisions to improve when the CO_2 concentration exceeds the threshold. In the future, the author will apply more advanced AI models such as Hybrid AI to improve CO_2 forecasting accuracy, expand the scale to the classroom system throughout the school, and integrate more sensors such as fine dust and VOC to comprehensively assess air quality.

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