IoT-Based Indoor Localization of Cigarette Smoke Using K-Nearest Neighbor and MQ-7 Sensors

Muhammad Qutham Najmi Abdillah[1], Anisa Ulya Darajat[2], FX Arinto Setyawan[3], Helmy Fitriawan[4]

Program Studi Teknik Elektro, Universitas Lampung, Bandar Lampung, Indonesia; email: anisa.ulya@eng.unila.ac.id*

[Received: 13 February 2026, Revised: 30 May 2026, Accepted: 31 May 2026]
Corresponding Author: Anisa Ulya Darajat

ABSTRACT — Due to the high prevalence of smoking among individuals aged 15 and older in Lampung Province and limited enforcement of smoke-free areas, a system was developed to detect and map smoker locations within a 4 × 3.42-meter room using four MQ-7 sensors. The K-Nearest Neighbor (KNN) algorithm classified smoke source locations based on carbon monoxide (CO) concentrations across four designated observation zones. Experimental results indicated that the system had an average sensor reading error of 2.041%. The classification process for smoker positions achieved 93.75% accuracy and displayed smoker locations in Zones 1, 2, 3, and 4 on a dashboard map. Detection and classification data were stored in the InfluxDB database and visualized online using Grafana. The system also delivered real-time values in parts per million (ppm), the status of each zone, and a ten-minute history of ppm values.

INTISARI — Tingginya prevalensi perokok di Provinsi Lampung dalam rentang durasi usia di atas 15 tahun dan terbatasnya pengawasan kawasan tanpa rokok. Maka, dikembangkanlah suatu sistem yang mampu mendeteksi dan memetakan lokasi perokok di dalam ruangan berukuran 4 × 3,42 meter dengan menggunakan empat buah sensor MQ-7. Metode K-Nearest Neighbor (KNN) diterapkan pada penelitian ini untuk mengklasifikasikan lokasi sumber asap berdasarkan kadar karbon monoksida (CO) pada empat zona pengamatan yang telah di tetapkan. Hasil pengujian menunjukkan bahwa sistem memiliki rata-rata kesalahan pembacaan sensor sebesar 2,041%. Proses klasifikasi posisi perokok mencapai tingkat akurasi sebesar 93,75% dan mampu menampilkan lokasi perokok pada Zona 1, 2, 3, dan 4 melalui tampilan denah pada dashboard. Data hasil deteksi dan klasifikasi lokasi perokok disimpan dalam basis data InfluxDB dan divisualisasikan secara daring menggunakan Grafana. Sistem juga mampu menampilkan nilai dalam satuan parts per million (ppm), status masing-masing zona, serta riwayat nilai ppm selama 10 menit terakhir.

KEYWORDS — Indoor smoke localization, MQ-7 sensor, K-Nearest Neighbor (KNN), Internet of Things (IoT), Real-time monitoring system.

I. INTRODUCTION

Cigarettes are tobacco products consumed by burning and inhaling tobacco materials, which contain various hazardous chemical substances such as tar, nicotine, arsenic, carbon monoxide (CO), and nitrosamines. These substances have adverse effects on human health [1], [2]. Exposure to cigarette smoke not only endangers active smokers but also passive smokers who inhale smoke from the surrounding environment. Indonesia has a high tobacco-use prevalence, with 34.5% of adults, or approximately 70.2 million people, using tobacco in 2021 [3]. One of the most dangerous components in cigarette smoke is carbon monoxide (CO), because it can interfere with hemoglobin's ability to bind oxygen in the bloodstream. Several regulations establish the Threshold Limit Value (TLV) for CO in workplaces at 25 ppm, with specific exposure limits depending on the duration of exposure [4], [5].

Previous research has developed cigarette smoke and air quality monitoring systems using gas sensors and microcontroller-based platforms. However, most existing studies focus primarily on detecting smoke presence or measuring gas concentrations based on fixed threshold values. Such threshold-based methods are often insufficiently adaptable, as cigarette smoke concentration varies with factors such as room size, air circulation, sensor placement, and the distance between the smoke source and the sensor. Previous smoke detection systems have generally focused on smoke presence detection and gas concentration measurement. Although these functions are important, they do not necessarily provide information about the position of the smoke source inside the monitored room. These limitations make the feasible deployment of smoke-monitoring systems more difficult, especially in indoor spaces divided into several zones. Many current strategies lack data recording in real time or video monitoring in order to supervise cigarette smoke. However, to solve the aforementioned problems, a combination of technologies, i.e., smoke detection, localization, data storage, and online data visualization, should be used to form an integrated system. Recent primary studies have also demonstrated the use of low-cost IoT sensor nodes and multi-gas sensing modules for continuous air-quality monitoring in indoor and environmental applications [6], [7], [8].

Differences in the threshold standardization of institutions may affect the determination of a certain threshold value for smoke exposure measurement. Therefore, a new, more flexible method is required to classify smoke level exposure. The KNN algorithm is employed in the proposed model due to its ability to classify new test data based on distances to previously existing training samples. With this classification system, smoke exposure levels and the source position will be determined without relying solely on a fixed threshold [9], [10], [11], [12].

As for Lampung Province, a consistently high smoking rate was recorded among people older than 15 years old during the last three years (33.43% in 2020, 34.07% in 2021, and 33.81% in 2022)[13]. Such circumstances increase the risks of secondhand smoke exposure among non-smokers, especially in smoke-free areas defined in Law of the Republic of Indonesia Number 36 of 2009 concerning Health [14]. Therefore, the development of a proper cigarette smoke detection and localization system is necessary to enforce smoke-free area requirements. Smoke-free area regulations are particularly vital in indoor spaces to prevent occupants from inhaling harmful cigarette smoke.

For this reason, this study proposes a novel approach based on a smoke detection and localization system for an indoor area measuring 4 × 3.42 m². This approach uses four MQ-7 sensors that work with the microcontroller [15], [16]. Classification will be performed using the KNN algorithm to detect the location of the smoke source based on CO concentration patterns measured by the sensors [10], [11], [17]. Furthermore, IoT-based online data visualization will be implemented in the proposed framework to enable online observation. Specifically, an IoT platform will include data transmission from MQ-7 sensors that measure carbon monoxide levels across different zones, a microcontroller that analyzes the collected data using the KNN algorithm, and a communication module that sends the data to an online database and displays it via an online interface.

This study presents a novel smoke detection and localization system for small indoor environments. The important aspect of the proposed system lies in the use of the KNN algorithm together with IoT. The proposed system makes use of visualization for online identification of the source of smoke in particular zones within the examined area. This study stands out from the existing methods because its aim is to find the source of the smoke.

II. RESEARCH METHODOLOGY

The research methods encompassed system design, hardware and controller development, testing software, and data processing. Data collection was conducted five times per zone. In each experiment, parts per million (ppm) measurements were taken every 10 seconds for 10 minutes. This produced 60 readings per experiment and 300 per zone. The four zones yielded a total of 1200 data points.

A. SYSTEM DESIGN

In the system design stage, the required components were selected according to system requirements, followed by wiring design and microcontroller programming. The system flowchart is shown in Figure 1.

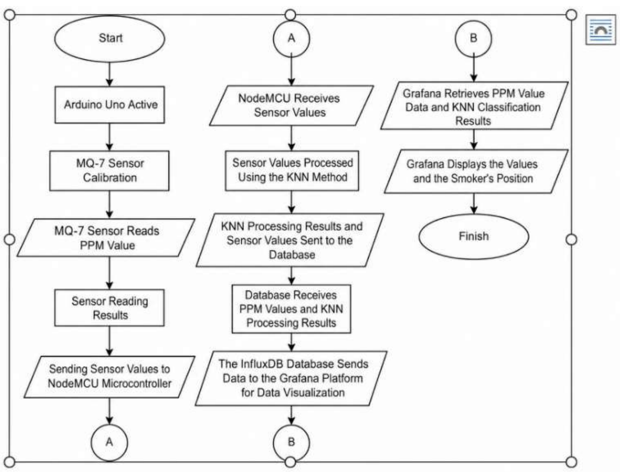

Figure 1. System Flowchart

Figure 1 presents the flowchart of the smoker position detection system. Once the Arduino Uno R3 microcontroller is turned ON, all sensors start acquiring data. Sensor data is communicated through serial communication from the Arduino Uno R3 microcontroller to the NodeMCU microcontroller. The NodeMCU then classifies the acquired sensor data using the K-Nearest Neighbor (KNN) algorithm. The classification outcomes are forwarded, along with sensor data, to the InfluxDB Time Series Database via the internet [8], [18]. Once stored in the database, InfluxDB communicates the sensor values to be visualized in the Grafana platform, enabling monitoring of the acquired sensor data and the location of the smoke source on the Grafana dashboard [19]. The smoke source detector device measures smoke concentration in ppm and identifies the location of the smoke source based on these values, classifying them within predefined zones in the room, as shown in Figure 2. The use of a time-series database and Grafana-based dashboard is also consistent with sensor-data monitoring implementations that store IoT data in InfluxDB and visualize it through Grafana [16], [19].

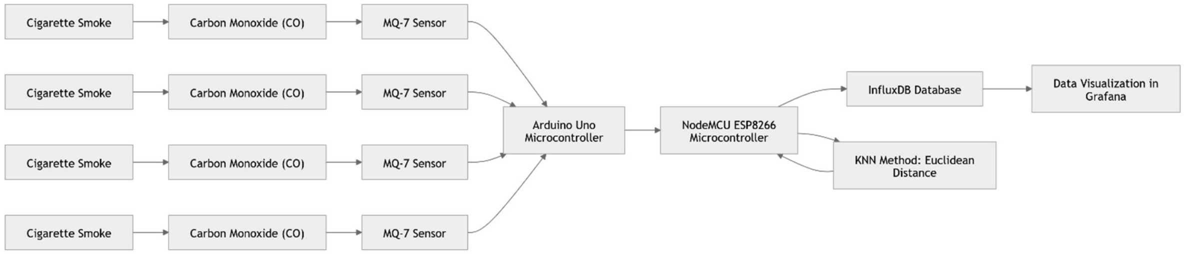

Figure 2. System Block Diagram

B. HARDWARE DESIGN

The input devices used in this experiment consist of four MQ-7 sensors. The information from the sensors is first stored on the Arduino Uno R3 microcontroller, then transmitted via the serial protocol to the NodeMCU microcontroller. The information is then sent to the InfluxDB database using Wi-Fi. There are four sensor placements, with the lab being divided into four parts.

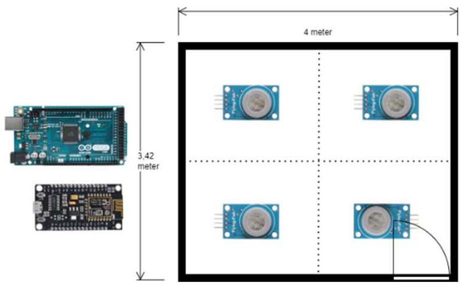

Figure 3. Sensor Placement Layout

The zones in which the sensors have been installed are shown in Figure 3 below, using the approach depicted in the monitoring interface. In each zone, there is one MQ-7 sensor that measures the ppm of cigarette smoke. This approach helps identify the accurate location from which the cigarette smoke emanates.

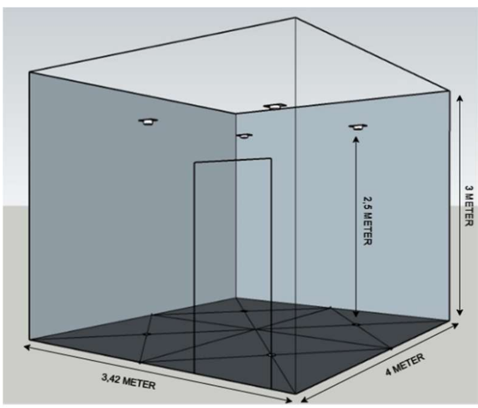

Figure 4. Room Zone Layout

Figure 4 depicts the 3D image of the room selected for this experiment. The dimensions of the room are 4 meters long, 3.42 meters wide, and 3 meters high. The four MQ-7 sensors are located in every zone at a height of 2.5 meters.

C. CONTROLLER DESIGN

The controller's design includes two steps: data collection and the use of the K-Nearest Neighbor algorithm. Data was collected indoors using MQ-7 calibrated sensors and Arduino Uno microcontrollers. The next step was to run various K values through the KNN algorithm. Value K=3 was chosen because it yielded optimal classification accuracy across all test scenarios. After finding the best K value, the K-Nearest Neighbor Algorithm was implemented in the NodeMCU program. It uses Euclidean distance calculations, which are described by Equation 1, [10], [12], [20]. The use of Euclidean distance in KNN is consistent with previous indoor localization studies that rely on distance-based similarity for location classification[17], [21].

$$euc = \sqrt{\sum_{i=0}^{n}(x_{2i} - x_{1i})^2} \tag{1}$$

with:

x_2 : testing data
x_1 : data sample
i : data variable
n : data dimension

Euclidean distances between the obtained ppm values (test data) and all the previously collected training data are calculated by the system. The goal is to distinguish the indoor locations of smokers. Classification is conducted by sorting smoke-originating zones (Zone 1-4) based on CO values. Classification into “smoke” and “no smoke” is the first task, whereas classification into smokers' locations is the final outcome.

D. SOFTWARE DESIGN

The software design in this study includes database design and configuration, as well as the design of the Grafana dashboard interface and the configuration of the database source in Grafana.

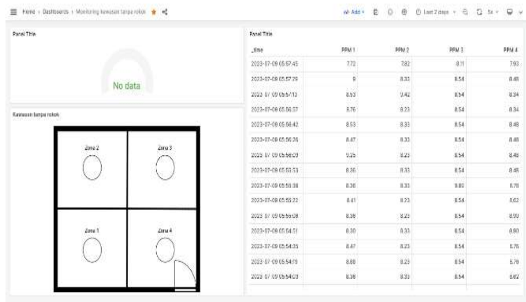

Figure 5. Dashboard Interface Design Result

Figure 5 presents the dashboard interface design. The dashboard includes three types of data visualizations. On the right, a table lists sensor readings from the past 10 minutes. In the upper-left corner, a real-time display shows the current ppm level in the room. In the lower right, a room layout visualization displays the condition of each monitoring zone.

III. RESULTS AND DISCUSSION

The position detector contains four MQ-7 sensors installed in various parts of the room for measuring CO in ppm. Information about CO in ppm measured by the sensors is sent to the Arduino Uno, then to the ESP8266 NodeMCU. This NodeMCU serves as an interface between the Arduino and Wi-Fi, implementing the K-Nearest Neighbors algorithm to detect smoke locations. CO concentration (ppm) and zone information are subsequently displayed on the Grafana panel through InfluxDB. The data collection interval is specified as 10 seconds. If there is no smoker in the room, a green light flashes on the screen. Conversely, a red light will be displayed on the screen indicating the smoker's location. The accuracy test checks the ppm outputs displayed in the Arduino serial monitor against manually calculated values based on the data in the MQ-7 sensor datasheet. A multimeter is used in this process. These results are presented in Table I.

TABLE I

RESULTS OF MQ-7 SENSOR READING ACCURACY EVALUATION

No	Voltage	PPM		*Error* (%)
		Sensor	Datasheet Calculation	
1	0.456	8.600	8.759	1.816
2	0.451	8.440	8.600	1.859
3	0.470	9.250	9.212	0.412
4	0.490	10.090	9.877	2.152
5	0.486	9.580	9.743	1.670
6	0.467	9.250	9.114	1.491
7	0.504	10.790	10.356	4.189
8	0.515	10.790	10.740	0.467
9	0.517	11.150	10.810	3.143
10	0.522	10.790	10.987	1.796
11	0.568	13.030	12.682	2.748
12	0.500	10.420	10.218	1.974
13	0.489	9.920	9.844	0.775
14	0.485	9.750	9.709	0.421
15	0.488	9.250	9.810	5.708
Overall Average Error				2.041

On average, the total error across 15 experiments, including those with and without cigarette smoke, was 2.041%. To calculate the algorithm's accuracy, the confusion matrix formula was used. Four experiments were done in each zone for 5 minutes after lighting a cigarette. The classification values were gathered from the Grafana dashboard.

TABLE II

KNN CLASSIFICATION RESULTS FOR ZONE 1

No	Zone 1 PPM Value (Classification)	Zone 2 PPM Value (Classification)	Zone 3 PPM Value (Classification)	Zone 4 PPM Value (Classification)
1	9.62(1)	8.76(0)	8.13(0)	9.24(1)
2	9.55(1)	8.06(0)	7.33(0)	8.06(0)
3	9.82(1)	9.00(0)	8.76(0)	9.73(1)

TABLE III

KNN CLASSIFICATION RESULTS FOR ZONE 2

No	Zone 1 PPM Value (Classification)	Zone 2 PPM Value (Classification)	Zone 3 PPM Value (Classification)	Zone 4 PPM Value (Classification)
1	8.85(0)	9.10(1)	9.20(0)	9.18(0)
2	8.54(0)	9.30(1)	7.34(0)	8.95(0)
3	8.55(0)	9.78(1)	8.60(0)	8.97(0)
4	8.98(0)	9.44(1)	8.60(0)	9.07(0)

TABLE IV

KNN CLASSIFICATION RESULTS FOR ZONE 3

No	Zone 1 PPM Value (Classification)	Zone 2 PPM Value (Classification)	Zone 3 PPM Value (Classification)	Zone 4 PPM Value (Classification)
1	8.94(0)	9.40(1)	9.35(1)	8.76(0)
2	8.76(0)	8.88(0)	9.35(1)	8.87(0)
3	8.29(0)	8.37(0)	10.48(1)	8.76(0)
4	9.17(0)	8.99(0)	10.04(1)	8.05(0)

TABLE V

KNN CLASSIFICATION RESULTS FOR ZONE 4

No	Zone 1 PPM Value (Classification)	Zone 2 PPM Value (Classification)	Zone 3 PPM Value (Classification)	Zone 4 PPM Value (Classification)
1	7.31(0)	6.55(0)	10.70(1)	15.32(1)
2	9.09(0)	9.01(0)	8.76(0)	9.51(1)
3	7.72(0)	8.54(0)	8.76(0)	9.33(1)
4	8.76(0)	9.00(0)	9.39(0)	9.38(1)

TABLE VI

CONFUSION MATRIX OF THE SYSTEM CLASSIFICATION RESULTS

Trial	TP (True Positive)	FP (False Positive)	FN (False Negative)	TN (True Negative)
Trial 1	1	1	0	2
Trial 2	1	0	0	3
Trial 3	1	1	0	2
Trial 4	1	0	0	3
Trial 5	1	0	0	3
Trial 6	1	0	0	3
Trial 7	1	1	0	2
Trial 8	1	0	0	3
Trial 9	1	0	0	3
Trial 10	1	1	0	2
Trial 11	1	0	0	3
Trial 12	1	0	0	3
Trial 13	1	0	0	3
Trial 14	1	0	0	3
Trial 15	1	0	0	3
Trial 16	1	0	0	3
Total	16	4	0	44

Tables 2 to 5 show the KNN classification results for Zones 1 to 4. In these tables, a value of 1 indicates that smoke is detected, while 0 indicates no smoke. The results from all zones were then used to form a confusion matrix and evaluate the accuracy of the KNN method. The confusion matrix results are presented in Table 6. From the test results, the system obtained 16 True Positive (TP), 4 False Positive (FP), 0 False Negative (FN), and 44 True Negative (TN) values. TP means the system correctly detected smoke when smoke was present. FP means the system detected smoke even though there was no smoke. FN means smoke was present but not detected, while TN means the system correctly identified that no smoke was present.

A total of 16 trials were conducted, and each trial produced four classification results based on the four zones. Therefore, there were 64 classification data points in total. The accuracy of the system was calculated using the following equation:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (2)$$

where:

$TP = 16$, $TN = 44$, $FP = 4$, $FN = 0$

Thus, the accuracy is:

$\text{Accuracy} = (16 + 44) / (16 + 44 + 4 + 0) = 60 / 64 = 93.75\%$

The Grafana dashboard displays data obtained from the InfluxDB bucket. The dashboard is refreshed every 10 seconds to show sensor readings, CO concentration in ppm, and the room layout indicating the detected smoke location. The smoke source is identified from the classification result in each zone. A value of 0 means no smoker is detected and the zone is shown in green. A value of 1 means smoke is detected and the zone is shown in red. Sensor accuracy was evaluated by comparing ppm values from the Arduino serial monitor with manual calculations based on the MQ-7 sensor datasheet. The manual calculation used the voltage-to-ppm equation, where the sensor output voltage was measured using a multimeter. The comparison results are presented in Table 1.

TABLE VII

DATA TRANSMISSION DELAY TIME

No	NodeMCU Transmission Time	InfluxDB Reception Time	*Delay*(s)
1	1:24:01	1:24:06	5.007
2	1:24:16	1:24:22	5.182
3	1:24:33	1:24:38	5.100
4	1:24:49	1:24:53	4.846
5	1:25:04	1:25:09	4.999
6	1:25:20	1:25:25	4.765
7	1:25:36	1:25:41	4.688
8	1:25:51	1:25:56	4.766
9	1:26:07	1:26:12	4.870
10	1:26:23	1:26:28	4.981
Average Delay (s)			4.920

Table 7 shows the results of the transmission delay test. The delay was measured as the time between when the data transmission command appeared in the NodeMCU serial monitor and when the data was received in the InfluxDB database. On average, the delay over 10 transmissions was 4.920 seconds.

Figure 6. Grafana Monitoring Dashboard Interface

Figure 6 shows the Grafana monitoring dashboard. A green indicator in the monitoring zone means there is no cigarette smoke, while a red indicator in Zone 1 shows that smoke is present. The dashboard works as expected.

Panel 1 shows the current parts per million (ppm) value. Zone 1 turns yellow if the value goes over 9 ppm. The dashboard uses green for values below 9 ppm, yellow for values above 9 ppm, and red for values above 12 ppm. Panel 2 shows where smoke was detected, and Panel 3 displays ppm data from the last 10 minutes.

TABLE VIII

SMOKER POSITION RESULTS ON THE MONITORING DISPLAY

Trial	Zona	PPM Value	Classification	Monitoring Layout	Conformity
Trial 1	1	9.55	1	Red	Match
	2	8.06	0	Green	Match
	3	7.33	0	Green	Match
	4	8.09	0	Green	Match
Trial 2	1	9.62	1	Red	Match
	2	8.76	0	Green	Match
	3	8.13	0	Green	Match
	4	9.24	1	Red	Match
Trial 3	1	8.54	0	Green	Match
	2	9.30	1	Red	Match
	3	7.34	0	Green	Match
	4	8.95	0	Green	Match
Trial 4	1	8.76	0	Green	Match
	2	8.88	0	Green	Match
	3	9.35	1	Red	Match
	4	8.87	0	Green	Match
Trial 5	1	8.94	0	Green	Match
	2	9.40	1	Red	Match
	3	9.35	1	Red	Match
	4	8.76	0	Green	Match

Table 8 presents the results of smoker position mapping on the monitoring interface. Each zone is shown in red when smoke is detected and green when no smoke is detected. The classification results generated by the KNN system in the microcontroller are displayed directly on the monitoring dashboard. The MQ-7 sensor produced an average measurement error of 2.041%, indicating that the sensor readings were reasonably accurate. The system was also able to detect and display the smoke source location in four predefined zones, namely Zones 1 to 4. Using the K-Nearest Neighbor (KNN) algorithm, the system achieved an overall classification accuracy of 93.75%. In addition, the monitoring platform provides real-time CO concentration in ppm, zone status, smoker location, and historical data from the last 10 minutes through the Grafana dashboard.

IV. CONCLUSION

The MQ-7 sensor had an average measurement error of 2.041%, showing it was highly accurate. The system also consistently found and displayed the smoke source in four set zones (Zones 1-4) on the monitoring dashboard. For smoke classification, the K-Nearest Neighbor (KNN) algorithm was used, achieving an overall accuracy of 93.75%. With these results, the monitoring platform showed real-time carbon monoxide (CO) levels in parts per million (ppm), a map of the area with zone status, and the latest 10-minute data in Grafana. The dashboard results matched the classification outcomes exactly.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest.

REFERENCES

[1] V. N. Zulaikhah, K. M. Z. Wijayadi, and E. Juliyanto, "Evaluasi Hasil Edukasi Masyarakat Tentang Bahaya Kandungan Dalam Rokok," *Indonesian Journal of Natural Science Education*, vol. 4, no. 2, pp. 510–515, 2021, doi: 10.31002/IJNSE.V4I2.1904.

[2] J. Saini, M. Dutta, and G. Marques, "Indoor Air Quality Monitoring Systems Based on Internet of Things: A Systematic Review," *International Journal of Environmental Research and Public Health 2020, Vol. 17, Page 4942*, vol. 17, no. 14, p. 4942, Jul. 2020, doi: 10.3390/IJERPH17144942.

[3] World Health Organization, "Ministry of Health and WHO release Global Adult Tobacco Survey Indonesia Report 2021," WHO Indonesia, Aug. 22, 2024. https://www.who.int/indonesia/news/detail/22-08-2024-ministry-of-health-and-who-release-global-adult-tobacco-survey-indonesia-report-2021

[4] Occupational Safety and Health Administration, "Carbon Monoxide," OSHA Occupational Chemical Database.https://www.osha.gov/chemicaldata/462.

[5] American Conference of Governmental Industrial Hygienists, "Carbon Monoxide," ACGIH. https://www.acgih.org/carbon-monoxide-3/.

[6] K. Kalaivani, S. Subramanian, G. K. S. Swedha, N. Vinoth, and V. Vishnu Priya, "Air Monitoring with Cloud and IoT," *International Conference on Sustainable Computing and Smart Systems, ICSCSS 2023 - Proceedings*, pp. 1027–1031, 2023, doi: 10.1109/ICSCSS57650.2023.10169619.

[7] F. Fitria, A. Khalid, E. Iryanie, and H. Heldalina, "IoT-Based Cigarette Smoke Monitoring System Using MQ135 Gas Sensor," *Formosa Journal of Computer and Information Science*, vol. 4, no. 2, pp. 115–126, Dec. 2025, doi: 10.55927/FJCIS.V4I2.15751.

[8] L. García, A. J. Garcia-Sanchez, R. Asorey-Cacheda, J. Garcia-Haro, and C. L. Zúñiga-Cañón, "Smart Air Quality Monitoring IoT-Based Infrastructure for Industrial Environments," *Sensors 2022, Vol. 22, Page 9221*, vol. 22, no. 23, p. 9221, Nov. 2022, doi: 10.3390/S22239221.

[9] L. T. Wong, K. W. Mui, and T. W. Tsang, "Updating Indoor Air Quality (IAQ) Assessment Screening Levels with Machine Learning Models," *International Journal of Environmental Research and Public Health 2022, Vol. 19, Page 5724*, vol. 19, no. 9, p. 5724, May 2022, doi: 10.3390/IJERPH19095724.

[10] N. Ali, D. Neagu, and P. Trundle, "Evaluation of k-nearest neighbour classifier performance for heterogeneous data sets," *SN Applied Sciences*, vol. 1, no. 12, Art. no. 1559, Dec. 2019, doi: 10.1007/s42452-019-1356-9.

[11] S. Uddin, I. Haque, H. Lu, M. A. Moni, and E. Gide, "Comparative performance analysis of K-nearest neighbour (KNN) algorithm and its different variants for disease prediction," *Scientific Reports 2022 12:1*, vol. 12, no. 1, pp. 6256-, Apr. 2022, doi: 10.1038/s41598-022-10358-x.

[12] A. Sanmorino, J. Alie, N. Ariati, and S. V. Wulanda, "K-NN Based Air Classification as Indicator of the Index of Air Quality in Palembang," *Sinkron: jurnal dan penelitian teknik informatika*, vol. 6, no. 3, pp. 853–859, Jul. 2022, doi: 10.33395/sinkron.v7i3.11469.

[13] Badan Pusat Statistik, "Persentase Penduduk Berumur 15 Tahun ke Atas yang Merokok Tembakau selama Sebulan Terakhir Menurut Provinsi," BPS Indonesia. https://www.bps.go.id/id/statistics-table/2/MTQzNSMy/persentase-merokok-pada-penduduk-umur---15-tahun-menurut-provinsi--persen-.html.

[14] Republic of Indonesia, "Law of the Republic of Indonesia Number 36 of 2009 concerning Health," 2009. https://peraturan.bpk.go.id/Details/38778/uu-no-36-tahun-2009.

[15] M. Taştan and H. Gökozan, "Real-Time Monitoring of Indoor Air Quality with Internet of Things-Based E-Nose," *Applied Sciences 2019, Vol. 9, Page 3435*, vol. 9, no. 16, p. 3435, Aug. 2019, doi: 10.3390/APP9163435.

[16] D. Wall, P. McCullagh, I. Cleland, and R. Bond, "Development of an Internet of Things solution to monitor and analyse indoor air quality," *Internet of Things*, vol. 14, p. 100392, Jun. 2021, doi: 10.1016/J.IOT.2021.100392.

[17] D. Ferreira, R. Souza, and C. Carvalho, "QA-kNN: Indoor Localization Based on Quartile Analysis and the kNN Classifier for Wireless Networks," *Sensors 2020, Vol. 20, Page 4714*, vol. 20, no. 17, p. 4714, Aug. 2020, doi: 10.3390/s20174714.

[18] J. Jo, B. Jo, J. Kim, S. Kim, and W. Han, "Development of an IoT-Based Indoor Air Quality Monitoring Platform," *J. Sens.*, vol. 2020, no. 1, p. 8749764, Jan. 2020, doi: 10.1155/2020/8749764.

[19] V. Nur Wijayaningrum, R. Wakhidah, T. Informasi, and P. Negeri Malang, "Monitoring Development Board based on InfluxDB and Grafana," *Telematika: Jurnal Informatika dan Teknologi Informasi*, vol. 20, no. 1, pp. 81–90, Mar. 2023, doi: 10.31315/telematika.v20i1.7643.

[20] R. Mussabayev, "Optimizing Euclidean Distance Computation," *Mathematics 2024, Vol. 12, Page 3787*, vol. 12, no. 23, p. 3787, Nov. 2024, doi: 10.3390/math12233787.

[21] S. Sadowski, P. Spachos, and K. N. Plataniotis, "Memoryless Techniques and Wireless Technologies for Indoor Localization with the Internet of Things," *IEEE Internet Things J.*, vol. 7, no. 11, pp. 10996–11005, Nov. 2020, doi: 10.1109/JIOT.2020.2992651.