JRAEE
Journal of Robotics, Automation, and Electronics Engineering
Vol. 4, No. 1, 2026, pp. 250-259
e-ISSN 3025-3780
https://journal.uny.ac.id/v3/jraee

Air Quality Classification Using the K-Nearest Neighbors Algorithm: A Case Study in Juwana District

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ARTICLE INFO

Article History
Received 12 Jan 2026
Revised 29 Aug 2026
Accepted 31 Aug 2026

Keywords
Air Quality Detector;
K-Nearest Neighbors;
Internet of Things;
Graphical User Interface;
Engineering Design Process.

ABSTRACT

Air quality is an important factor in maintaining human health and environmental sustainability. Increasing transportation activity in Pati Regency contributes to higher air-pollutant emissions. This study develops a real-time air-quality monitoring and classification system using the K-Nearest Neighbors (KNN) algorithm. The system uses MQ-7, MQ-135, and SDS011 sensors to measure CO, CO_2, PM2.5, and PM10 concentrations. Measurement data are transmitted to Firebase Realtime Database and classified through a graphical user interface using Euclidean distance. Experimental results show that the system achieves 83% accuracy, 85% precision, 83% recall, and an F1-score of 82%. These results indicate that the proposed system can provide reliable real-time air-quality information for environmental monitoring applications.

ABSTRAK

Kualitas udara merupakan faktor penting dalam menjaga kesehatan manusia dan keberlanjutan lingkungan. Peningkatan aktivitas transportasi di Kabupaten Pati turut berkontribusi terhadap meningkatnya emisi pencemar udara. Penelitian ini mengembangkan sistem pemantauan dan klasifikasi kualitas udara secara real-time menggunakan algoritma K-Nearest Neighbors (KNN). Sistem menggunakan sensor MQ-7, MQ-135, dan SDS011 untuk mengukur konsentrasi CO, CO_2, PM2.5, dan PM10. Data hasil pengukuran dikirim ke Firebase Realtime Database dan diklasifikasikan melalui antarmuka grafis menggunakan jarak Euclidean. Hasil pengujian menunjukkan bahwa sistem mencapai akurasi 83%, presisi 85%, recall 83%, dan F1-score 82%. Hasil tersebut menunjukkan bahwa sistem mampu memberikan informasi kualitas udara secara real-time untuk mendukung pemantauan lingkungan.

1. Introduction

Air quality is a crucial indicator for assessing environmental health and public well-being. In Indonesia, rising industrial, transportation, and urbanization activity has driven a marked increase in air-pollutant emissions. These pollutants are known to directly affect human health, particularly the respiratory system, and to reduce quality of life, especially in urban and industrial areas. Air quality in Indonesia has declined significantly, particularly in densely populated urban regions with heavy transportation activity, where the main source of particulate matter is motor-vehicle emissions, including combustion products and component friction.

Beyond carbon monoxide, fine particulates such as PM2.5 and PM10 are also a major concern in air pollution. PM2.5 and PM10 are microscopic particles with diameters below 2.5 micrometers (μm) and below 10 micrometers, respectively. According to the World Health Organization [1], the recommended limit for fine particulates (PM2.5) is 5 $\mu g/m^3$ as an annual average and 15 $\mu g/m^3$ as a 24-hour average, whereas the safety threshold applied by the Indonesian government is 50 $\mu g/m^3$ for both the 24-hour and annual averages. For PM10, WHO recommends an annual limit of 15 $\mu g/m^3$ and a daily limit of 45 $\mu g/m^3$. Data from Indonesia's Meteorology, Climatology, and Geophysics Agency (BMKG) [2] indicate that average air quality in Indonesia frequently falls into the “Moderate” to “Unhealthy” category, particularly in densely populated areas such as Juwana District.

According to data published by the Central Bureau of Statistics (BPS) of Pati Regency, the population of Juwana District had reached 97,507 people by mid-2022 across an area of approximately 55.93 km^2 [3], making Juwana one of the most densely populated districts in Pati Regency, at 1,743 people per km^2. This rapid population growth has directly increased mobility needs, which in turn has driven significant growth in the number of motor vehicles. According to the Central Bureau of Statistics of Central Java Province, the number of motor vehicles in Pati Regency reached 718,265 units, consisting of 57,694 cars, 1,362 buses, 25,636 trucks, and 633,573 motorcycles [4]. This increase in motor vehicles has contributed substantially to air pollution through exhaust emissions containing hazardous pollutants.

Accordingly, this study classifies air quality in Juwana District to provide a clear picture of the region's air-quality conditions. It applies a data-mining approach, using the K-Nearest Neighbors (KNN) algorithm as the classification method for its demonstrated ability to achieve high accuracy even with a relatively small dataset [5]. KNN is an effective classification method for predicting air quality, particularly when the available data are limited, since it classifies new data based on their proximity to previously categorized data. The results of this classification are expected to serve as a basis for air-pollution mitigation policy recommendations for the Juwana District government.

2. Problem-Solving Approach

2.1 Air Quality Detector

An air quality detector is a technology-based device designed to monitor ambient air conditions by detecting and measuring the concentration of specific pollutants. The system operates by using various sensors to obtain air-quality data, which is then processed and presented informatively. An air quality detector is intended to provide early information about pollution levels, helping protect human health and supporting environmental control and management efforts. Technologies commonly applied in such systems include gas and particulate sensors, microcontrollers, the Internet of Things, and graphical user interfaces [6].

2.2 Internet of Things

The Internet of Things (IoT) is a technology paradigm that integrates physical objects with the internet, enabling those objects to automatically collect, exchange, and process data [7]. Devices within an IoT system are typically equipped with sensors, actuators, and communication capabilities that support real-time monitoring and control, supported by technologies such as cloud computing to turn the generated data into valuable information. As a result, IoT adoption supports improved efficiency, accuracy, and data-driven decision-making across a wide range of fields.

Some examples of IoT applications in ambient air monitoring are as follows.

- Air quality monitoring: IoT sensors can be installed in urban or industrial areas to monitor pollutant concentrations in real time.
- Early pollution warning: IoT technology enables systems to issue notifications or early warnings when pollutant concentrations exceed defined thresholds.
- Environmental management and evaluation: air-quality data collected by IoT sensors can be stored and

ISSN 3025-3780 (online)
ISSN 3025-4590 (printed)

analyzed to evaluate pollution trends over time.

2.3 Graphical User Interface

A Graphical User Interface (GUI) is a graphics-based interface that enables interaction between users and a system through visual elements such as icons, buttons, menus, and other graphical displays. A GUI is designed to make a system easier to operate, present information intuitively, and improve the effectiveness and efficiency of monitoring and control processes. It also serves as the link between the data generated by a system and its users, so that information can be presented in real time in a form that is easy to understand and that supports decision-making.

The following are applications of a GUI in ambient air monitoring.

- Air-quality data monitoring: the GUI displays air-quality sensor readings in real time, allowing users to track conditions directly.
- Information visualization: the GUI presents air-quality data as charts, indicators, or tables so that the information is easier to understand and analyze.
- Hazard warnings: the GUI can display notifications or alerts when pollutant values exceed set thresholds, allowing users to take prompt action.
- Decision support: the information presented through the GUI helps users evaluate air-quality conditions and supports fast, well-informed decision-making.

3. Research Design

This study applies the Engineering Design Process (EDP), a systematic framework used to design and develop a product or system in a structured manner [8]. The EDP method was selected for its advantage in breaking each stage of the process down in greater detail, as shown in Fig. 1.

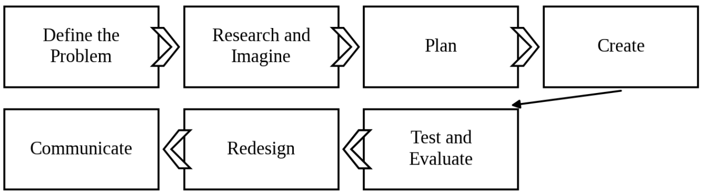

Fig.1 Engineering design process

3.1 Define the Problem

Define the Problem is the process of identifying and analyzing the problem underlying the study, namely the high level of air pollution in Juwana District. This condition creates a need for an accurate, reliable air-quality classification system that is readily accessible to the public and relevant stakeholders.

3.2 Research and Imagine

At this stage, the hardware, software, and supporting equipment used in the study were identified, as shown in Tables 1 and 2.

Table 1. Hardware List

No	Hardware	Function
1	ESP32 DevKIT V1	Used as the microcontroller.
2	MQ-7 Sensor	Selected to detect CO gas.
3	MQ-135 Sensor	Used to measure CO2.
4	SDS011 Sensor	Selected to detect dust-particle levels such as PM2.5 and PM10 [9].
5	Step-Down Module 5V	Needed to step down the voltage to match the operational requirements of the sensors and microcontroller.
6	TP4056 Module	Used as a practical and efficient battery-charging module.
7	Solder	Used to connect electronic components so they are properly joined.
8	Multimeter	Plays an important role in measuring voltage, current, and resistance in electronic components.
9	Mini Drill	Needed during assembly, since the system integrates several sensors that must be combined onto a single circuit board.
10	Laptop	Used as the center for development, programming, and data analysis.

Table 2. Software List

No	Software	Function
1	Tinkercad	Used for 3D modeling of the hardware box.
2	Fritzing	Used because it can visualize electronic circuits in both schematic and PCB-layout form.
3	Arduino IDE	Used to program the hardware.
4	JupyterLab	Used to train the KNN model.
5	Firebase	Used to store the data transmitted by the hardware.

3.3 Plan

At this stage, the system was planned comprehensively as the basis for the subsequent design process, including the preparation of a block diagram. Fig. 2 illustrates the block diagram of the air-quality classification system, which is divided into three parts: Hardware, Database, and Data Classification. In the hardware section, the system is designed to detect air-quality parameters using several sensors: the MQ-7 sensor for carbon monoxide (CO) levels, the MQ-135 sensor for other pollutant gases such as carbon dioxide (CO_2), and the SDS011 sensor for measuring particulate concentrations such as PM2.5 and PM10, consistent with calibration and validation practice for low-cost gas and particulate sensors [10].

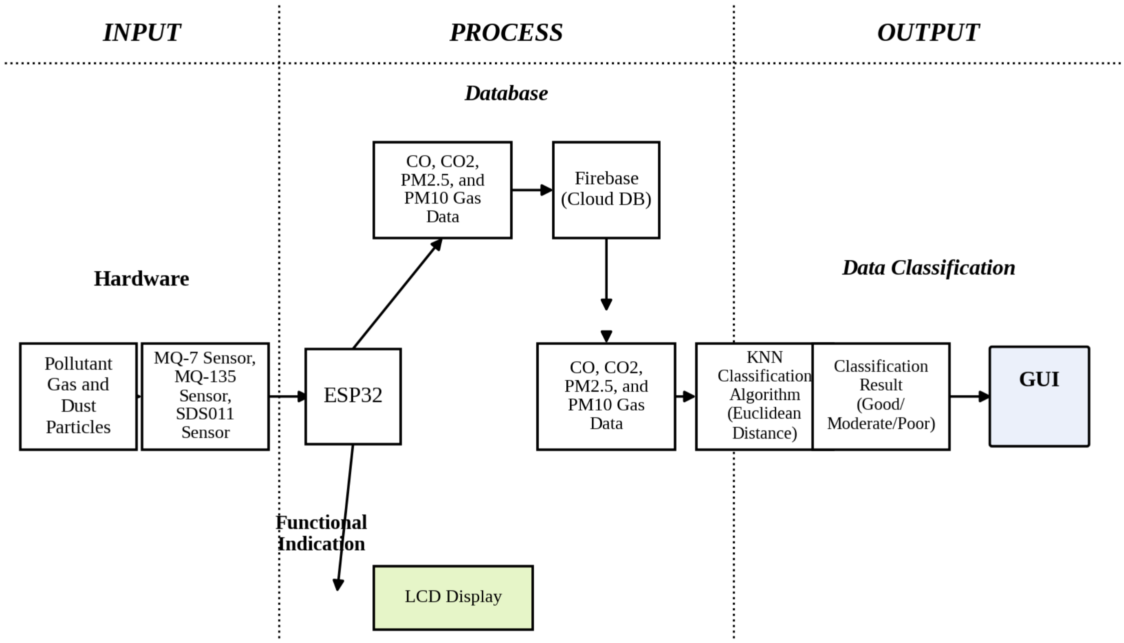

Fig. 2 Block diagram

In the database section, the data collected from these sensors is transmitted in real time to a cloud database platform (Firebase). Firebase is used to store air-quality parameter data, including CO, CO_2, PM2.5, and PM10, in a structured format.

In the data-classification stage, the system retrieves the data stored in Firebase and processes it using the K-Nearest Neighbors (KNN) algorithm. The KNN algorithm works by comparing new input data against training data labeled “Good,” “Moderate,” and “Poor” based on nearest distance. These class labels are assigned according to previously defined air-quality thresholds, used as the criteria for categorizing air-quality conditions consistent with the applicable air-quality standard [11]. The air-quality threshold details for each category are presented in Table 3.

Table 3. Air Quality Threshold Indications

PM2.5 (μg/m³)	PM10 (μg/m³)	CO (PPM)	CO2 (ppm)	Status
0.0–12.0	0–54	0–25	0–700	Good
12.1–35.4	55–154	26–50	701–1000	Moderate
35.5–55.4	155–254	51–100	1001–1500	Poor

3.4 Create

Journal of Robotics, Automation, and Electronics Engineering
Vol. 4, No. 1, 2026, pp. 250-259
ISSN 3025-3780 (online)
ISSN 3025-4590 (printed)

At this stage, a prototype air-quality monitoring system was built by integrating the hardware and software. This prototype was constructed based on the design established during the planning stage, so that each selected component could be implemented according to its function. On the hardware side, the work involved assembling the circuit, fabricating and printing the PCB, mounting the components, and conducting initial testing to confirm the performance of each module. On the software side, the work involved writing the program code, implementing the classification algorithm, and integrating the system so that the hardware could communicate optimally with the GUI. The resulting prototype is intended to represent the system design in physical form and to be ready for testing in the next stage.

3.5 Test and Evaluate

This stage covers the testing and evaluation of the developed system prototype. Functional testing was carried out to confirm that each hardware component, software component, and the system as a whole operated according to the design. Hardware testing involved evaluating the sensors by comparing their readings against a reference instrument to confirm data accuracy, as well as testing the step-down module and the TP4056 module to confirm voltage stability and charging function. Software testing covered the software functions and the graphical user interface (GUI) to confirm that data processing, storage, and visualization operated correctly. System testing, meanwhile, evaluated the performance of the KNN algorithm in classifying air quality using the study's dataset, comprising a total of 137 records split into 70% training data and 30% test data. To obtain optimal model performance, hyperparameter tuning was carried out using the GridSearchCV method to determine the best parameter values [12]. In addition, the model was evaluated using k-fold cross-validation to improve generalization and minimize overfitting to the training data [13].

3.6 Communicate

This stage covers the complete system design, development process, and research findings, communicated clearly and systematically to relevant stakeholders through written reports, presentations, or scientific publications.

4. Results and Discussion

4.1 Create Stage Implementation

Hardware integration was carried out by placing the electronic components inside a 3D-printed casing. Assembly began with mounting the PCB as the base of the circuit, followed by connecting the components neatly and systematically. The component layout was arranged to be stable, safe, and easy to maintain, while each connection was positioned so as not to interfere with the others, making efficient use of the available space inside the box. The resulting hardware box is shown in Fig. 3.

Fig. 3 Hardware box display

To support user interaction, a Graphical User Interface was developed using libraries such as Tkinter or PyQt. This GUI displays air-quality sensor values in real time, covering the CO, CO2, PM2.5, and PM10 parameters. The air-quality classification result is displayed visually as text or a color indicator denoting the category (good, moderate, or poor). The GUI also provides a classification-history feature, displayed as a table, which can be exported to CSV format for further analysis or documentation. The GUI display is shown in Fig. 4.

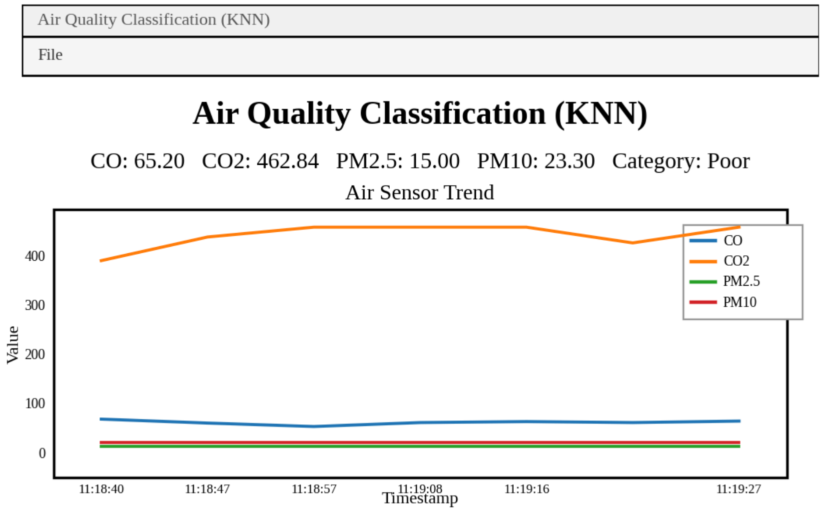

Fig. 4 GUI display

4.2 Test and Evaluate Stage Implementation

Table 4 presents the results of training the KNN model using 137 training records labeled by air-quality category (Good, Moderate, and Poor), containing the CO, CO2, PM2.5, and PM10 parameters. Before use, the data was normalized with a Standard Scaler to equalize the scale across features, improving classification accuracy. During KNN classification testing, the value of the parameter k was obtained by searching across the range k = 1–20 using a grid-search method, with k = 3 producing the highest accuracy. In addition, model validation was performed using 5-fold cross-validation so that the resulting classification was more stable and not dependent on a single data subset; k = 3 means the system determines a class based on the three nearest neighbors. Of the 137 records available, 96 were used as training data and 41 as test data, consistent with the 70:30 training–testing split. Evaluation showed an accuracy of 83%; a precision of 85%; a recall of 83%; and an f1-score of 82%.

Table 4. Classification Report (KNN)

	precision	*recall*	*f1-score*	*support*
Good	0.78	0.88	0.82	8
Moderate	0.81	0.92	0.86	24
Poor	1.00	0.56	0.71	9
accuracy			0.83	41
macro avg	0.86	0.78	0.80	41
weighted avg	0.85	0.83	0.82	41

The Confusion Matrix in Fig. 5 was used to evaluate the types of errors made by the model, showing the number of correct and incorrect predictions for each category – for example, whether the model more frequently misclassified air quality as “Good,” “Moderate,” or “Poor.”

Journal of Robotics, Automation, and Electronics Engineering
Vol. 4, No. 1, 2026, pp. 250-259
ISSN 3025-3780 (online)
ISSN 3025-4590 (printed)

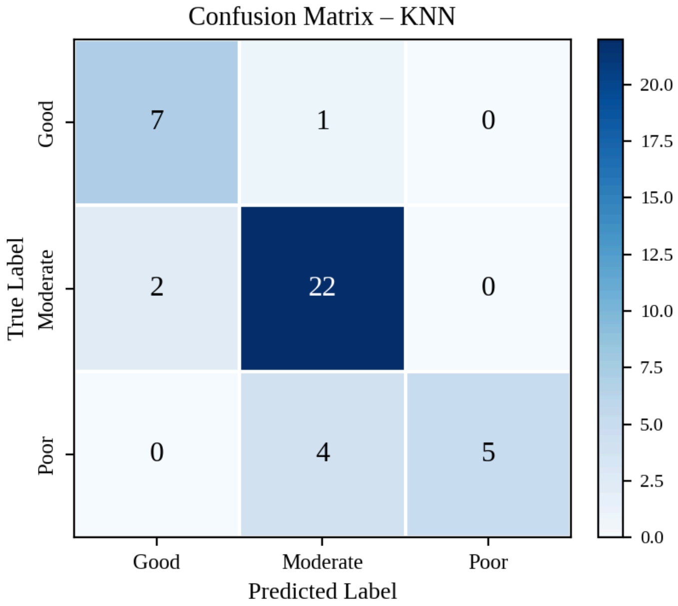

Fig. 5 Confusion matrix

- 7 records that were actually "Good" were correctly predicted as "Good" (True Positive for the "Good" class).
- 2 records that were actually "Moderate" were incorrectly predicted as "Good" (False Negative for the "Moderate" class).
- Only 1 record that was actually "Good" was incorrectly predicted as "Moderate" (False Positive for the "Good" class).
- 4 records that were actually "Poor" were incorrectly predicted as "Moderate" (False Positive for the "Moderate" class).
- 22 records that were actually "Moderate" were correctly predicted as "Moderate" (True Positive for the "Moderate" class).
- 5 records that were actually "Poor" were correctly predicted as "Poor" (True Positive for the "Poor" class).

The results above show that the KNN model performs reasonably well, particularly for the "Moderate" and "Good" classes, as reflected in the high True Positive counts and very low False Negative counts. For the "Poor" class, however, some misclassification remains: 4 records that should have been "Poor" were instead predicted as "Moderate." This is attributable to similarities in data characteristics, particularly given the imbalanced distribution of the data, indicating that although the model is fairly accurate overall, its performance on the minority class still has room for improvement.

Fig. 6 shows the Receiver Operating Characteristic curve for the KNN model in classifying air quality into three categories: "Good," "Moderate," and "Poor." The test results show that the "Good" class achieved an AUC value of 0.972, indicating very strong performance, as the model was able to distinguish this class with a high degree of accuracy. The "Moderate" class achieved an AUC value of 0.860, while the "Poor" class achieved an AUC of 0.854. The resulting weighted-average AUC was 0.881, placing the classification accuracy of this study within the "Good Classification" category [14].

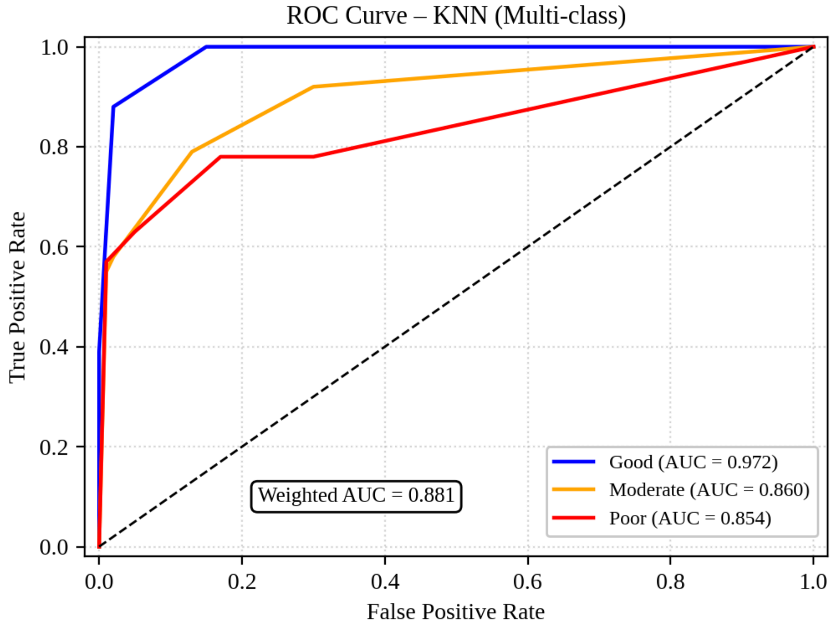

Fig. 6 Receiver operating characteristic curve

4.3 Redesign Stage Implementation

At the redesign stage, an additional 3D-printed component was added to cover the edges of the openings in the hardware enclosure. This addition was intended to improve the neatness and aesthetics of the device and to protect its internal components.

4.4 Communicate Stage Implementation

At this stage, the results of the device implementation were reported comprehensively. Testing was carried out by placing the device at four different locations in Juwana District with contrasting environmental characteristics. The sensor readings were then processed by the classification system to determine the air-quality category at each location – "Good," "Moderate," or "Poor" – based on the previously defined gas and particulate concentration thresholds shown in Table 3. The classification history, presented in tabular form, can be downloaded in CSV format for further analysis or as documentation of the test results.

The first test was conducted in the Alun-Alun Juwana (town square) area. Based on the sample data obtained, shown in Table 5, the classification results indicate that the "Moderate" category was dominant, with PM2.5 the most influential parameter in the classification outcome.

Table 5. Classification Results at Location 1 (Alun-Alun Juwana)

Timestamp	CO	CO2	PM2.5	PM10	Category
08:37:24	58.24837	505.78915	22.1	36.9	Moderate
08:37:33	42.73223	544.86188	22.7	37.3	Moderate
08:55:26	32.14607	558.32928	22.4	37.9	Moderate
08:57:26	25.66893	551.56757	16.2	19.2	Moderate
08:58:46	37.92812	592.98737	17.8	20.3	Moderate
08:59:46	22.89186	565.14728	17.0	21.9	Moderate
09:00:46	22.89186	538.21191	16.8	23.0	Moderate
09:01:46	24.98453	505.78915	21.7	65.0	Moderate
09:02:46	22.83829	551.56757	21.0	52.3	Moderate

The second test was conducted in front of SMK BTB Juwana. Based on the sample data obtained, shown in Table 6, the classification results indicate that the "Moderate" category was dominant, with PM2.5 the most critical parameter influencing the classification outcome.

Table 6. Classification Results at Location 2 (SMK BTB Juwana)

Timestamp	CO	CO2	PM2.5	PM10	Category
09:57:19	13.91927	551.56757	21.6	28.6	Moderate
09:58:29	13.24391	544.86188	21.0	26.9	Moderate
09:59:39	13.71874	531.61743	20.4	25.5	Moderate
10:01:49	13.79876	544.86188	20.8	25.7	Moderate

ISSN 3025-3780 (online)
ISSN 3025-4590 (printed)

10:02:19	13.51979	505.78915	21.3	27.5	Moderate
10:03:29	13.55945	525.07825	20.9	26.7	Moderate
10:04:39	13.32242	512.16437	20.7	28.4	Moderate
10:05:49	13.40118	499.46823	20.2	27.9	Moderate

The third test was conducted in the Pasar Juwana (market) area, a location with substantial pedestrian and vehicle activity. Based on the sample data obtained, shown in Table 7, the classification results indicate that the "Moderate" category was dominant, with PM2.5 the most critical parameter influencing the classification outcome.

Table 7. Classification Results at Location 3 (Pasar Juwana)

Timestamp	CO	CO2	PM2.5	PM10	Category
09:53:59	20.10632	592.98737	15.4	24.9	Moderate
09:54:09	18.22607	585.94171	15.8	24.3	Moderate
09:55:19	20.35523	544.86188	15.3	23.5	Moderate
09:56:29	21.21512	614.47131	16.2	24.4	Moderate
09:57:39	19.85921	578.95325	17.1	29.1	Moderate
09:58:49	17.21230	565.14728	16.8	28.6	Moderate
09:59:59	17.39415	585.94171	15.5	25.3	Moderate
10:00:09	18.41399	578.95325	14.7	22.8	Moderate
10:01:19	16.58437	551.56757	15.4	20.9	Moderate

The fourth test was conducted along Jalan Toko Horizcom, Juwana, a location with lighter vehicle traffic but still containing a substantial amount of airborne dust. Based on the sample data obtained, shown in Table 8, the classification results indicate that the "Moderate" category was dominant, with PM2.5 the most critical parameter influencing the classification outcome.

Table 8. Classification Results at Location 4 (Jalan Toko Horizcom, Juwana)

Timestamp	CO	CO2	PM2.5	PM10	Category
09:33:03	5.45842	439.18259	13.8	15.9	Moderate
09:34:13	7.44745	444.97568	13.8	18.2	Moderate
09:34:23	6.38359	450.82056	13.7	17.2	Moderate
09:35:33	6.53985	486.98785	13.4	16.3	Moderate
09:36:43	5.49009	480.82803	13.5	17.4	Moderate
09:37:53	5.01033	474.72113	13.1	17.8	Moderate
09:38:03	4.99525	499.46823	12.8	17.5	Moderate
09:39:13	4.92020	505.78915	13.8	20.0	Moderate
09:40:23	5.47424	538.21191	14.9	21.1	Moderate

5. Conclusion

The results of this study show that the air-quality monitoring system was successfully designed and implemented through the integration of sensor hardware, a Firebase Realtime Database for data storage and synchronization, and a Graphical User Interface for visualization and user interaction. This integration enables the acquisition, transmission, storage, and display of air-quality data to occur in real time and in a centralized manner, allowing the system to operate stably and in accordance with its intended design.

In terms of data processing, the KNN algorithm was able to classify air quality with an accuracy of 83% on the test data. Evaluation of model performance using weighted-average metrics showed a precision of 85%, a recall of 83%, and an f1-score of 82%. These values indicate that the model achieves a good balance between its ability to recognize each class and the accuracy of its classification results, and demonstrate consistent performance in classifying air-quality categories in Juwana District based on the parameters used.

Author Contribution:

All authors contributed equally as the main contributors to this paper. All authors read and approved the final manuscript.

Funding:

This research received no external funding.

Acknowledgement:

The authors thank the Department of Electrical and Electronics Engineering, Vocational Faculty, Universitas Negeri Yogyakarta, for providing the facilities used in this research.

Conflicts of Interest:

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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