

IoT-based Spatiotemporal Smart Air Quality Monitoring and Analysis System with a Machine Learning Approach

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ABSTRACT

Air quality plays an important role in the sustainability of life, especially for humans. Human activities, such as industry and motorised vehicles, have increased air pollution, particularly fine particulates (PM_{1.0}, PM_{2.5}, PM₁₀) and carbon monoxide (CO), which have serious impacts on health. In Bandung City, the Environmental Agency recorded high levels of pollution, so a real-time air quality monitoring system is needed. This research aims to develop an Internet of Things (IoT)-based air pollution monitoring system in various locations in Bandung, focusing on spatial-temporal analysis during weekdays and weekends. The IoT sensors used are capable of detecting pollutants such as PM_{1.0}, PM_{2.5}, PM₁₀, and CO, thus enabling continuous air quality monitoring. Based on the average Air Pollution Standard Index (ISPU) scores, the monitored locations show that CO pollution levels are higher than PM. Besides, PM particulates and CO are dominant on weekdays. The result of model prediction between LSTM and GRU model is GRU model having low value based on RSME and MRE indicator and making it a better model. The system was successfully designed and implemented, allowing air quality data and analysis results to be accessed in real-time through a website that is easy to use by the public.

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1. INTRODUCTION

Air pollution in urban and industry areas has produced emissions of various hazardous substances that can be detrimental to health. Some of the particles that are harmful are fine particulates such as PM_{1.0}, PM_{2.5}, PM₁₀, as well as carbon monoxide that are usual byproducts of human activity. Air pollution mainly comes from transportation emissions which contain almost 60% carbon monoxide (CO), around 15% hydrocarbons, and the rest are particulates [1]. WHO states that most of the global population (99%) breathes air that contains high levels of pollutants, exceeding WHO guidelines. In 2021, 6.5 million early deaths globally were caused by air pollution [2]. Based on PM_{2.5} particulate indicator in 2023, Air Pollution Index in Bandung City has been on the verge towards unhealthy category, 70% of this is due to transportation gas emissions, and the rest are from residential activity (like trash burning), factory and power plant smokestacks, as well as other sources [3]. Data Centre for Research on Energy and Clean Air (CREA) reports of declining air quality in Indonesia. In 2023, air quality across Indonesia has reached an unhealthy and even dangerous level. Actions across sectors is key to quell air pollution [4].

Based on the aforementioned urgency, this research aims to build an air quality monitoring system that focuses on four main pollutants namely PM_{1.0}, PM_{2.5}, PM₁₀, and CO by monitoring forum

locations in Bandung City i.e. Universitas Pendidikan Indonesia Faculty of Mathematics and Natural Science Campus in the Setiabudi area that represents office areas, Hegarmanah area that represents populated area, Summarecon area that represents industrial and settlement areas, and Cileunyi area that represents transportation dense areas which covers main roads with traffic. This research also low-costs sensors that can detect pollutants and also equipped with sensors for environmental data such as temperature, humidity, and air pressure. Furthermore, this research aims to establish a real-time air pollution dataset in Bandung City, creating a system that can monitor air pollution in Bandung City in real-time and analyse concentration patterns of air pollution based on spatial analysis (area) and temporal (weekdays and weekends). Subsequently, the gathered dataset is used for training a machine learning algorithm to derive daily predictions of air quality in Bandung City.

Research on Particulate Matter in Serbia [5] shows that the implementation of a large-scale low-cost sensor network is very effective in providing real-time information and early warnings of pollution, both daily and episodic. In line with the systematic review [6] on the use of the Internet of Things (IoT) in air pollution monitoring, IoT-based applications have proven to be a reliable and economical alternative. In an effort to obtain particle pollution data, a previous study [7] has compared the performance of the Nova Fitness SDS011 and Plantower PMSA003 models. As a development, this study chooses the ZH03B sensor as an alternative instrument.

The data that is used is time-series data, namely data that is observed and taken sequentially over time. To get a future prediction value, a model that is capable of capturing patterns and complex temporal time dependencies from data is required. Recurrent Neural Network (RNN) is a machine learning method that is designed specifically for sequential data [8] and is suitable to capture the dynamic nature of the atmospheric environment [9]. However, standard RNN has limitations in retaining long-term information. Therefore, this research uses more advanced variants of RNN, namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU).

LSTM is a sophisticated model that is widely used for air quality predictions [8]. By using a gate mechanism, LSTM is able to solve short term memory problems and effectively learns long-term dependencies in time-series data [8], [9], [10]. This capability makes it a powerful technique to characterize behaviors in time series data on environmental modelling applications [10]. On the other hand, GRU is a variant of RNN that is simpler compared to LSTM, having fewer gates, and often shows a faster learning process with competitive performances [9]. Numerous research have shown that deep learning models like LSTM and GRU significantly outperforms conventional statistical models (such as VARIMA) [9] as well as other conventional machine learning models (such as MLP and SVM) [10] in prediction accuracy for environmental data. As an example, latest research by Ng et al. [9] has successfully compared performances of LSTM and GRU in predicting PM_{2.5} concentrations, but does not include gas pollutants like carbon monoxide (CO) in their analysis. Therefore, this research not only confirms the effectiveness of these models, but also contributes to expanding the scope of analysis by including CO, which is a significant pollutant in urban environments. A comparative summary of previous studies on air pollutant forecasting using various modeling techniques is presented in Table 1.

Table 1. Summary of previous studies on air pollutant forecasting

Reference	Model	Metrics	Pollutans	Best Model
[11]	1. LSTM	R ²	CO, NO, NO ₂ , SO ₂ , PM ₁₀ , NH ₃ , O ₃ , PM _{2.5}	1. Bi-LSTM (CO, NO, NO ₂ , SO ₂ , PM ₁₀ , NH ₃)
	2. Bi-LSTM			
	3. GRU			
	4. MLP			2. GRU and LSTM (O ₃ , PM _{2.5}).
	5. XGBoost			
[9]	1. LSTM	RMSE, MAE, MAPE	PM _{2.5}	1. LSTM
	2. GRU			2. GRU
	3. VARIMA			
[12][13]	1. DT	RMSE, MB, R ² , MAE, Accuracy	PM _{2.5} , PM ₁₀ , NO ₂ , O ₃ , CO	1. GRU (PM _{2.5})
	2. RF			2. Bi-LSTM (PM ₁₀)
	3. MLP			3. M-CNN-Bi-LSTM (NO ₂)
	4. GB			
	5. SVR			4. LSTM (O ₃ , CO)
	6. CNN			

Reference	Model	Metrics	Pollutans	Best Model
[14]	7. GRU	Bias, RMSE, MAE, CVG	NO ₂ , PM ₁₀ , PM _{2.5}	Random Forest
	8. GRUx2			
	9. LSTM			
	10. LSTMx2			
	11. LSTM-GRU			
	12. Bi-LSTM			
	13. CNN-LSTMv1			
	14. CNN-LSTMv2,			
	1. Linear Model			
	2. Additive Model			
	3. Hierarchical spatio-temporal models			
	4. Random Forest			
	Shallow Learning			
	1. Random Forest			
[15]	2. KNN	Accuracy, F1 Score, Precision, Recall, UAC	PM ₁₀	Deep Learning(LSTM, GRU, RNN, CNN)
	3. WKNN			
	4. SVM			
	5. ANN			
	Deep Learning			
	1. LSTM			
	2. GRU			
	3. RNN			
	4. CNN			
	1. Random Forest			
[16]	2. Decision Tree	R	AQI, PM _{2.5}	1. MLP 2. LSTM
	3. KNN			
	4. MLP			
	5. LSTM			
	1. Linear Regression			
[17]	2. DT/RF	R, RMSE, MAE	PM _{2.5}	LightGBM
	3. GBR			
	4. SVR			
	5. XGBoost			
	6. LighGBM			

Based on previous research that analyzes air pollution on weekdays and weekends in Surabaya City [18] that studies the concentration of PM₁₀ and TCP, results show that pollutant concentration is higher, exceeding quality standards, on weekdays, while pollutant concentration on weekends meets quality standards. Other research [19] analyzes carbon monoxide (CO) pollution levels at Jakarta Sudirman Street, which is a location with high traffic density. The research predicts CO concentrations on full work days, half work days, and weekends. Shown results indicate CO concentrations higher on work days.

Therefore, this research aims to analyze results of air pollution monitoring in Bandung City. Analyzing spatial-temporal air pollution is key to understanding variations of pollution from time to time and in various locations, which can help identify patterns, trends, and the influence of human activity such as traffic and industrial activity on air quality. This information guides decision making on effective policies, better city planning, as well as public awareness on factors that influence pollution and the steps of health protection. With spatial-temporal data, pollution control strategy can be optimized, and environment management can be done in a more sustainable manner.

However, despite the growing number of studies on air quality monitoring and forecasting, several limitations can still be identified. Most existing studies focus on individual pollutants, particularly particulate matter such as PM_{2.5} or PM₁₀, while gas pollutants like carbon monoxide (CO) are often excluded from integrated deep learning analyses. Furthermore, limited attention has been given to understanding the comparative behavior of recurrent neural network models across pollutants with different characteristics using real-time IoT-based data. Therefore, this study aims to address these gaps by developing an IoT-based real-time air quality monitoring system using low-cost sensors across multiple urban zones in Bandung City, constructing a multi-pollutant spatiotemporal dataset (PM_{1.0}, PM_{2.5}, PM₁₀, and CO), and comparatively analyzing the forecasting performance of LSTM and GRU models to examine their behavior across spatial and temporal contexts.

2. METHOD

Phases of this research are mapped with research design illustrated in Figure 1. Phases carried out in this research consists of problem formulation, literature study, IoT controller design and implementation, data collection from monitoring device, data preprocessing, concluding with a comparative analysis of air pollution from four locations (spatial) and in weekdays as well as weekends (temporal).

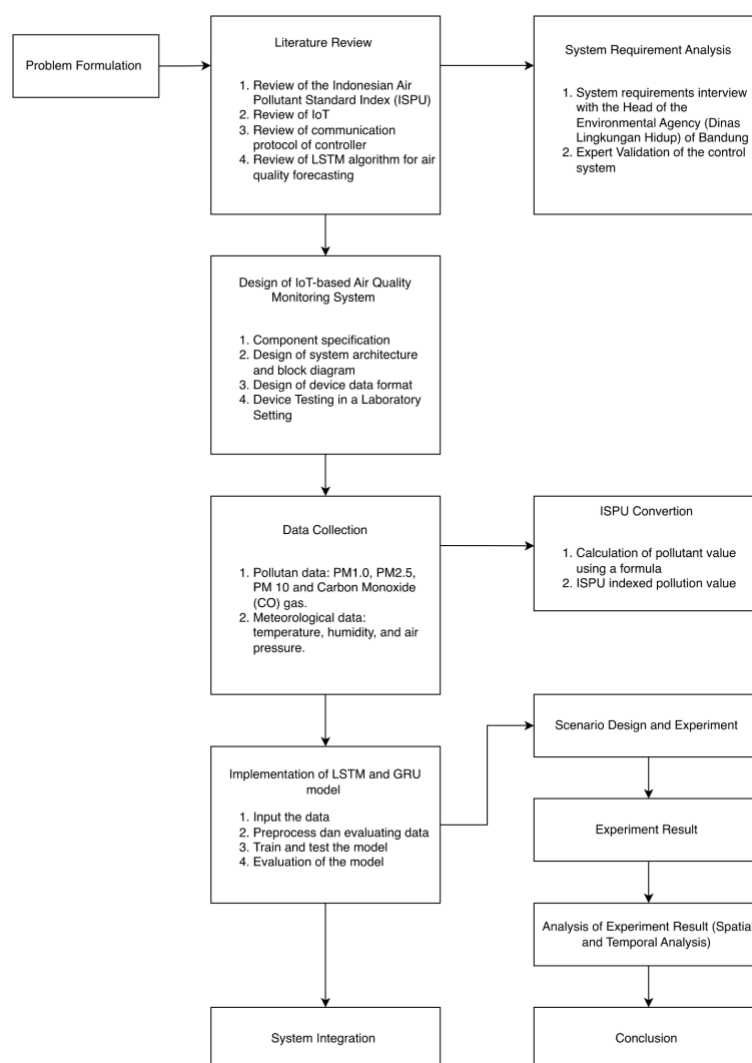


Figure 1. Research Method

Figure 1 illustrates the overall research process for developing Internet of Things (IoT)-based air quality monitoring system for four regions in Bandung City, combined with machine learning prediction using LSTM and GRU algorithms.

Below is a detailed description of each research stage:

1. Problem formulation

The study begins with identifying the research problem and objectives such as how to design an IoT-based air quality monitoring system capable of collecting real-time pollutant data and predicting air quality levels using LSTM and GRU.

2. Literature review
This stage includes several theoretical studies related to:
 - a. ISPU as a reference for classifying air quality levels,
 - b. The concept of IoT and its implementation in environmental monitoring,
 - c. Communication protocols used by microcontrollers to transmit sensor data,
 - d. The LSTM and GRU used for air quality forecasting based on time series data
3. System Requirements Analysis
System requirements are analyzed through interviews with the Environmental Agency (Dinas Lingkungan Hidup) of Bandung to identify necessary parameters and standards, and expert validation of the proposed control system to ensure reliability.
4. Design of an IoT-Based Air quality monitoring
This stage focuses on designing the IoT system, which includes:
 - a. Component specification (sensors, microcontrollers, and communication modules).
 - b. System architecture and block diagram design.
 - c. Device data format design.
 - d. Laboratory testing of the device to verify sensor accuracy and functionality before field deployment.
5. Data collection
The system collects data from four areas in Bandung city, consisting of pollutant data (PM_{1.0}, PM_{2.5}, PM₁₀, and Carbon Monoxide), Meteorological data: temperature, humidity, and air pressure. All data is transmitted automatically via IoT network to the server for further processing and analysis.
6. ISPU Conversion
Raw sensor data are converted into standardized ISPU values through calculation of pollutant concentrations using official formulas and determination of pollution categories (Good, Moderate, Unhealthy, etc) based on ISPU index threshold.
7. Implementation of LSTM and GRU models
This stage focuses on predictive modeling using machine learning with several steps such as:
 - a. Data input: collected sensor data are prepared for training
 - b. Preprocessing: data cleansing, normalization, formatting for model input, and data evaluation.
 - c. Training and testing: the LSTM and GRU models are trained and evaluated using historical air quality data.
 - d. Model evaluation: accuracy is assessed using metrics such as RMSE or MAE to compare performances.
8. System Integration
Both the IoT monitoring system and prediction models are integrated into a web-based platform, allowing real-time monitoring and air quality forecasting to be viewed simultaneously.
9. Scenario Design and Experiment
Experimental scenarios are designed to test system performance under different environmental conditions across the four monitoring regions.
10. Experiment Result
This stage presents the results of field and laboratory experiments, showing the system's data accuracy and the performance of both LSTM and GRU models.
11. Analysis of experimental results
The results are analyzed to evaluate and compare the predictive accuracy of the models and the reliability of the IoT system in real-time air quality monitoring. In addition, at this stage, spatial and temporal analysis was carried out on the data obtained to describe the conditions of the area studied based on the results of pollutant value measurements.
12. Conclusion
The final stage concludes the research findings, summarizing:
 - a. The effectiveness of the IoT-based air quality monitoring system.
 - b. The accuracy of LSTM and GRU models in forecasting air pollution.
 - c. Recommendations for future improvements and system scalability.

2.1. Research Location

This research was conducted in Bandung City, particularly in four location spots in accordance with the criteria for air quality monitoring locations by Peraturan Menteri Lingkungan Hidup dan

Kehutanan Nomor 14 Tahun 2020 [20], air quality monitoring locations is classified into: a) transportation dense areas that covers main roads with dense traffic; b) industrial area; c) densely populated settlements; and d) office areas that are not directly influenced by transportation. The four locations of this research are as follows.

- a. FPMIPA UPI, representing office areas that are not directly influenced by transportation
- b. Hegarmanah, representing densely populated settlements
- c. Summarecon, representing industrial areas or regions
- d. Cileunyi, representing transportation dense areas that cover main roads with dense traffic.

2.2. Materials and Equipment

Materials and equipment used in this research includes:

1. YD-ESP32-S3 Microcontroller: used as the center of data processing in air quality monitoring systems.
2. ZH03B Sensor: used to measure air pollution levels in the form of PM pollutants.
3. MQ-7 Sensor: used to measure air pollution levels in the form of CO.
4. DHT22 Sensor: used to measure temperature and humidity.
5. BME280 Sensor: used to measure air pressure.
6. Other hardware and components include: wifi module, cables, resistors, capacitors, and electrical power source.
7. Software: includes software for programming microcontrollers, data processing, machine learning implementation and user interface.

2.3. Requirements Analysis

In this phase, a requirement analysis is conducted to determine objective, function, and system features that will be developed. Requirements analysis involves technical specification of hardware and software that are going to be used, as well as user requirements and user environment.

1. User Requirements
 - a. Intuitive User Interface
A user interface that is easy to use so that information can be accessed by various groups.
 - b. Real-time Monitoring
The system provides accurate, real-time data and can be accessed anytime.
 - c. Accessibility
Can be accessed using various devices, including smartphones and computers.
2. User Environment
The environment of this system is in Bandung. The system calculates various air pollution that may occur.

2.4. Modelling Phase

In this study, the GRU and LSTM models were implemented using PyTorch, while data preprocessing performed was using scikit-learn. Data normalization was performed using the StandardScaler to ensure comparable feature scales prior to training. To ensure a fair comparison, both models were trained and evaluated using identical hyperparameter settings.

2.4.1. LSTM

The architecture of the Long Short-Term Memory (LSTM) has been described in previous studies [9]. In general, the architecture begins with a forget gate, as expressed in (1), that regulates which information should be retained or removed from the cell state. This gate employs a recurrent activation function to map the input values into the range of $[0, 1]$, where values close to zero indicate information to be discarded, while values closer to one indicate information to be preserved. Subsequently, the input gate determines which new information should be incorporated into the cell state by using a combination of recurrent and hyperbolic tangent activation functions. The resulting updated

information is stored in the current cell state, as expressed in (4). Finally, the output gate generates the output of the unit based on both the input and the updated cell state. The produced output is split into two parts, where one part contributes to the updated cell state, while the other forms the hidden state, as expressed in (6), which is propagated to the next unit or used for prediction.

$$f_t = \sigma(W_{hf} h_{t-1} + W_{xf} x_t + b_f) \quad (1)$$

$$u_t = \sigma(W_{hu} h_{t-1} + W_{xu} x_t + b_u) \quad (2)$$

$$C_t = \tanh(W_{hc} h_{t-1} + W_{xc} x_t + b_c) \quad (3)$$

$$C_t = f_t \cdot h_{t-1} + u_t \cdot C_t \quad (4)$$

$$o_t = \sigma(W_{ho} h_{t-1} + W_{xo} x_t + b_o) \quad (5)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

2.4.2. GRU

Similar to LSTM, GRU employs gating mechanisms to control the flow of information through the hidden state, enabling the model to capture long-term dependencies in sequential data [9]. However, unlike LSTM, which utilizes three gates, GRU adopts a simpler architecture consisting of only two gates, namely the reset gate and the update gate, making it computationally more efficient.

The reset gate controls the extent to which past information from the previous hidden state should be forgotten, while the update gate determines how much of the previous hidden state is retained and how much new information is incorporated. At each time step, t , the GRU takes as input the current input vector, $x_t \in R^{n \times d}$, and the hidden state from the previous time step, $h_{t-1} \in R^{n \times d}$, where n denotes the number of samples, d the number of input features, and h the number of hidden units. Both gates are computed using fully connected layers followed by sigmoid activation functions, which map the inputs to values in the range $[0,1]$.

Based on the reset gate, a candidate hidden state is generated using a hyperbolic tangent activation function to ensure that its values lie within the interval $[-1,1]$. When the reset gate values approach one, the candidate hidden state incorporates information from both the current input and the previous hidden state. Conversely, when the reset gate values approach zero, the influence of the previous hidden state is suppressed. The update gate then determines the final hidden state by balancing the contribution of the previous hidden state and the candidate hidden state. When the update gate value is close to one, the hidden state remains largely unchanged, whereas values close to zero allow the candidate hidden state to dominate. Through this gating mechanism, GRU effectively mitigates the vanishing gradient problem encountered in standard RNNs and enhances the modeling of long-range temporal dependencies.

$$r_t = \sigma(x_t W_{xr} + h_{t-1} W_{hr} + b_r) \quad (7)$$

$$z_t = \sigma(x_t W_{xz} + h_{t-1} W_{hz} + b_z) \quad (8)$$

$$\hat{h}_t = \tanh(x_t W_{xh} + (r_t \odot h_{t-1}) W_{hh} + b_h) \quad (9)$$

$$h_t = r_t \odot h_{t-1} + (1 - z_t) \odot \hat{h}_t \quad (10)$$

2.5. Model Evaluation

Model performance was evaluated based on RMSE and MSE value on both models. During hyperparameter tuning, the optimal configuration was determined by minimizing RMSE and MSE values. These metrics use total of test data, n , to get deviation of actual and predicted data at a time, t . RMSE is expressed as in (12) and MSE is expressed as in (11).

$$MSE = \frac{1}{n} \sum_{t=1}^n (\hat{Y}_t - Y_t)^2 \quad (11)$$

$$RMSE = \sqrt{MSE} \quad (12)$$

3. RESULT AND DISCUSSION

This section presents the dataset construction, data collection, exploratory data analysis (EDA), spatial data, and temporal analysis. The air quality data were obtained during the monitoring period, from July 2, 2025 to September 13, 2025.

3.1. Data Construction

After the data were obtained from the monitoring devices located across the Bandung region, the dataset was constructed. Initially, raw data were subjected to a cleaning process. This step

addressed data incompleteness, duplicate, and inconsistent. The issue of data incompleteness was resolved by either imputation or deletion to ensure data integrity. Next, the cleaned data was standardized for uniformity across all variables. The process included converting the measurement unit to the same metric system and ensuring a consistent time format.

3.2. Data Collection

To collect data, four IoT devices were placed on 4 points in Bandung. Using the sensor of those devices, the pollutants were monitored in realtime. The pollutants were PM_{1.0}, PM_{2.5}, PM₁₀, and Carbon Monoxide(CO) Gas. From the devices, pollutant and meteorological data were obtained, such as temperature, humidity, air pressure, etc. Through the use of this IoT system, the data collection was enabled in real-time and continuous manner. Furthermore, the data were transmitted from each device at a 30-second interval. The total amount of data collected was 559.217 records, spanning a continuous monitoring period, from July 2, 2025, to September 13, 2025. Next, the collected data was stored to cloud service to analyze further and used to predict air quality in near future. Table 2 presents the information from collected data.

Table 2. Data Information

Poin	Start Date	Total Record	Total Resample Based on Hour	Total days
Hegarmanah	2025-07-14	142414	1195	49.79
Cileunyi	2025-07-14	178668	1429	59.54
Summarecon	2025-08-07	109418	912	38
FPMIPA UPI	2025-07-29	128717	1075	33.79

Table 2 presents the dataset derived from the monitoring devices, totaling 559.217 records and comprising sensor id, datetime, PM_{1.0}, PM_{2.5}, PM₁₀, CO, temperature, humidity, and pressure. These data were then explored further and analyzed spatially and temporally

3.3. Data Preprocessing

At this stage, preprocessing was performed on the input data intended for the training and testing phases. This processing step was intended to remove inconsistencies data, transform data from JSON format to tabular by extracting and flattening to separate columns, and remove irrelevant attributes from the dataset. The following presents the raw data collected from the IoT devices.

```

1- 1
2  "ID": "4",
3-  "sensor": {
4-    "ZH03B": {
5      "PM1.0": 0,
6      "PM2.5": 0,
7      "PM10.0": 0
8    },
9-    "BME280": {
10     "Temperature": 21.04,
11     "Pressure": 710.5574,
12     "Altitude": 2874.951,
13     "Humidity": 88.31055
14   },
15-    "DHT22": {
16     "Temperature": 19.3,
17     "Humidity": 76.4,
18     "HeatIndex": 19.28044,
19     "DewPoint": 15.06139,
20     "ComfortRatio": 61.56905,
21     "ComfortStatus": 10
22   },
23-    "MQ7": {
24     "PPM": 351.2079
25   }
26 },
27-  "dateTime": {
28    "date": "2025-07-07",
29    "time": "14:36:36"
30  }
31 }

```

Figure 2. String JSON

Next, the JSON string as shown in Figure 2. is parsed, transformed, and mapped into separate used attributes, such as id_sensor, datetime, pm1, pm25, pm10, co, temperature, humidity, and pressure. The following presents extracted and mapped data.

Table 3. Subset of Feature Extraction Results

Message	Sensor ID	Datetime	PM _{1.0}	PM _{2.5}	PM ₁₀	CO	Temperature	Humidity	Pressure
{"ID": "4", "sensor": {"ZH03B": {"PM1.0": 0, "PM2.5": ...	4	2025-07-07 14:36:36	0	0	0	351.2079	19.3	76.4	710.5574
{"ID": "3", "sensor": {"ZH03B": {"PM1.0": 26, "PM2.5": ...	3	2025-07-07 14:36:38	26	32	36	135.2020	19.5	71.4	692.5986
{"ID": "4", "sensor": {"ZH03B": {"PM1.0": 0, "PM2.5": ...	4	2025-07-07 14:37:06	0	0	0	351.4026	19.2	76.5	710.5574
{"ID": "3", "sensor": {"ZH03B": {"PM1.0": 24, "PM2.5": ...	3	2025-07-07 14:37:08	24	30	34	82.32714	19.5	71.4	692.5986
{"ID": "4", "sensor": {"ZH03B": {"PM1.0": 0, "PM2.5": ...	4	2025-07-07 14:37:36	0	0	0	351.7923	19.2	76.5	710.5574

After extracting data, data was subjected to the cleaning process to remove “Message” column, cast “Datetime” column from string to be datetime data type, and cast “Sensor Id” column from string to be integer as Table 4. Moreover, there was transformed the resampling data on the “CO” column to convert R_0 value as Figure 3. This transformation is intended to adjust for differences in R_0 during the experiment due to differences in R_0 at the time of data collection. The following presents the cleaning data results.

```
# perbaikan r0
# Tentukan tanggal batas
cutoff = pd.to_datetime("2025-08-21")

# Mask untuk data sampai tanggal cutoff
mask = data['sensor_data_1']['datetime'] <= cutoff

# Update hanya baris yang sesuai mask
data['sensor_data_1']['co'] = (
    data['sensor_data_1'].loc[mask, 'co'] * 2.24 / 54.14
)

data['sensor_data_2']['co'] = data['sensor_data_2']['co'] * 2.57 / 64.17
data['sensor_data_3']['co'] = data['sensor_data_3']['co'] * 0.65 / 16.26
data['sensor_data_4']['co'] = data['sensor_data_4']['co'] * 0.09 / 5.30
```

Figure 3. Data Resampling Process

Table 4. Subset of Cleaning Data Results

Datetime	Sensor ID	PM _{1.0}	PM _{2.5}	PM ₁₀	CO	Temperature	Humidity	Pressure
2025-08-21 10:00:00	1.0	20.916667	26.225000	29.325000	0.078207	26.785000	48.042500	911.739647
2025-08-21 11:00:00	1.0	24.341667	30.358333	34.000000	0.081298	28.310000	46.360833	910.793810
2025-08-21 12:00:00	1.0	16.208333	20.466667	22.758333	0.084379	29.647500	44.293333	910.006130
2025-08-21 13:00:00	1.0	10.858333	13.933333	15.366667	0.082616	27.686667	46.332500	909.217984
2025-08-21 14:00:00	1.0	10.583333	13.558333	14.841667	0.083833	26.297500	48.868333	908.522641
2025-08-21 15:00:00	1.0	25.083333	29.866667	32.325000	0.088224	25.770000	51.321667	908.396065
2025-08-21 16:00:00	1.0	12.916667	16.333333	18.333333	0.097692	25.166667	53.150000	908.410967
2025-08-21 17:00:00	1.0	19.473684	24.526316	27.526316	0.069431	20.942105	67.636842	916.921289
2025-08-21 18:00:00	1.0	18.308333	23.141667	25.783333	0.072410	21.855833	66.290833	917.470797

Datetime	Sensor ID	PM _{1.0}	PM _{2.5}	PM ₁₀	CO	Temperature	Humidity	Pressure
2025-08-21 19:00:00	1.0	17.470588	22.193277	24.613445	0.077847	22.071429	66.416807	917.615528
2025-08-21 20:00:00	1.0	20.925000	26.350000	29.475000	0.084980	22.000833	66.730000	918.231056
2025-08-21 21:00:00	1.0	21.566667	27.016667	30.200000	0.086362	21.995833	67.143333	918.922332
2025-08-21 22:00:00	1.0	19.325000	24.450000	27.358333	0.086089	21.800833	68.274167	919.183940
2025-08-21 23:00:00	1.0	34.966667	43.400000	48.808333	0.092157	21.640833	68.892500	918.926388

3.4. The Analysis of The Forecasting Model

The analysis of the forecasting models was conducted using identical hyperparameter values for both models. The model was evaluated based on RMSE and MSE value on both models. RMSE and MSE were selected as the primary performance metrics because they are highly effective at penalizing large errors, thus providing a comprehensive measure of the model's predictive accuracy. Moreover, the model's accuracy could not be fully assessed due to the continuous nature of the output variable. Because RMSE and MSE give error metrics, the experiment results by changing the hypermeter value have to achieve the minimum RMSE and MSE value. The optimal hyperparameter settings obtained and the evaluating results were presented in the following table.

Table 5. Hyperparameter

Hyperparameter	LSTM	GRU
Loss function	RMSE	RMSE
Activation function	Tanh	Tanh
Recurrent activation	Sigmoid	Sigmoid
Optimiser	Adam	Adam
Number of hidden layers	2	2
Number of units	64	64
Dropout	0	0
Number of epochs	80	80
Batch size	4	4
Number of time steps	20	20

Table 6. PM_{1.0} Sensor Evaluation

Point	Parameter	LSTM	GRU
Hegarmanah	RMSE	4.395884	3.399925
	MSE	19.323792	11.559487
Cileunyi	RMSE	1.617407	1.274247
	MSE	2.616006	1.623704
Summarecon	RMSE	2.370218	2.319740
	MSE	5.617933	5.381192
FPMIPA UPI	RMSE	3.242352	2.868431
	MSE	10.512844	8.227899

Table 7. PM_{2.5} Sensor Evaluation

Point	Parameter	LSTM	GRU
Hegarmanah	RMSE	5.502634	3.952216
	MSE	30.278985	15.620015
Cileunyi	RMSE	1.812813	1.580147
	MSE	3.286289	2.496864
Summarecon	RMSE	3.103065	2.883937
	MSE	9.629014	8.317093
FPMIPA UPI	RMSE	4.212586	3.490362
	MSE	17.745883	12.182626

Table 8. PM₁₀ Sensor Evaluation

Point	Parameter	LSTM	GRU
Hegarmanah	RMSE	5.985561	4.523851
	MSE	35.826946	20.465232
Cileunyi	RMSE	2.202524	1.769805
	MSE	4.851110	3.132211
Summarecon	RMSE	3.312779	3.357307
	MSE	10.974502	11.271509
FPMIPA UPI	RMSE	4.846796	3.928382
	MSE	23.491436	15.432189

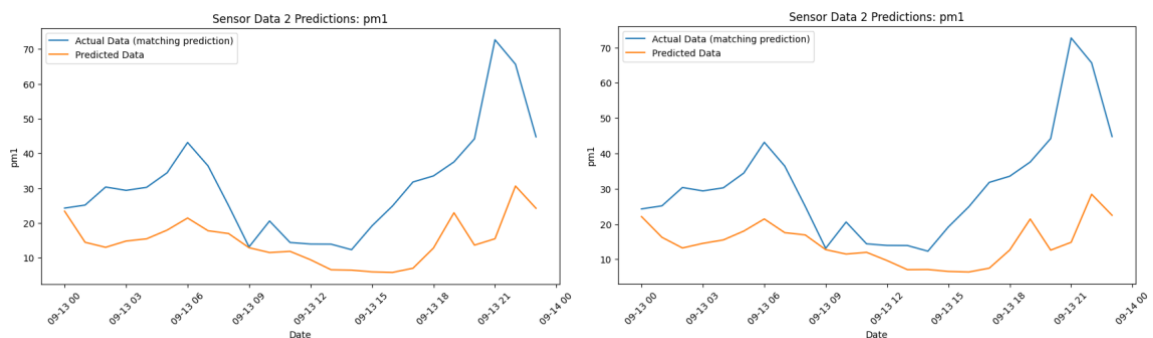
Table 9. CO Sensor Evaluation

Point	Parameter	LSTM	GRU
Hegarmanah	RMSE	0.281533	0.256844
	MSE	0.079261	0.065969
Cileunyi	RMSE	0.021471	0.010835
	MSE	0.000461	0.000117
Summarecon	RMSE	0.005637	0.004992
	MSE	0.000032	0.000025
FPMIPA UPI	RMSE	0.041650	0.026027
	MSE	0.001735	0.000677

Table 10. Mean Value of Sensor Evaluation

Sensor	Parameter	LSTM	GRU
PM _{1.0}	RMSE	2.90646525	2.46558575
	MSE	9.51764375	6.6980705
PM _{2.5}	RMSE	3.6577745	2.9766655
	MSE	15.23504275	9.6541495
PM ₁₀	RMSE	4.086915	3.39483625
	MSE	18.7859985	12.57528525
CO	RMSE	0.08757275	0.0746745
	MSE	0.02037225	0.016697
All sensors	RMSE	2.684681875	2.2279405
	MSE	10.88976431	7.236050563

Based on the RMSE value, both models present that the RMSE value of the forecasting model is under 10.00. This value indicates a high level of performance, suggesting only minimal deviation of the predicted values from the actual values. Furthermore, although the deviation of LSTM and GRU model is slight, the error value of LSTM is lower than GRU, except for the PM₁₀ sensor in Summarecon. The underlying cause cannot be conclusively determined from the current experimental setup.

Figure 4. Comparison of PM_{1.0} Forecasting Plots. (a) Plot of the LSTM Model Results (b) Plot of the GRU Model Results

Based on the forecasting plot, Figure 4, the forecasting result of LSTM and GRU showed a negligible difference. Nevertheless, based on the mean value of all sensors as reported in Table 10, the RMSE and MSE value of GRU model is consistently lower than LSTM model. This observation is in line with the findings in [9], which reported that GRU and LSTM outperform VARIMA, while further indicating a marginal performance advantage of GRU over LSTM in this study. Although the improvement is relatively small, the GRU model demonstrates slightly better predictive performance

compared to the LSTM model. Therefore, within the scope of this forecasting task and experimental setting, GRU can be considered a more appropriate model than the LSTM model.

3.5. Spatial Analysis

Spatial analysis used is comparative spatial analysis, this analysis compares pollutant levels between multiple spatial points (in this case, four monitoring locations). It focuses on identifying differences or similarities in average pollutant concentrations across locations. The method used is descriptive statistics by location with computing the mean, median, and standard deviation of pollutant concentrations at each location and spatial comparison visualization using some of charts such as choropleth maps (GIS) at Figure 5 or bar charts (Figure 6) or to visualize the mean values spatially and highlight differences. Table 11 describes the result of descriptive statistics by location that represented by the average concentrations for each pollutant at the four locations are as follows:

Table 11. Actual Measurement Results in All Four Locations

Location	Pollutant	mean	Median	Min	Max	ISPU mean
Hegarmanah	PM _{1.0}	17.590448	16	0	1000	47.231504
	PM ₁₀	24.643674	22	0	1000	24.388118
	PM _{2.5}	22.15385	20	0	1000	54.900219
	CO	6.015057	0.130308	0.023714	35.90244	108.429681
Cileunyi	PM _{1.0}	25.040322	22	0	257	58.843872
	PM ₁₀	35.109924	31	0	372	33.35398
	PM _{2.5}	31.267835	28	0	315	67.74247
	CO	15.069521	14.82305	11.15963	39.68209	277.340215
Summarecon	PM _{1.0}	19.454477	17	0	85	49.559535
	PM ₁₀	27.297136	24	0	122	26.725959
	PM _{2.5}	24.442322	22	0	105	57.507353
	CO	9.365664	9.172488	5.555125	15.29184	112.450409
FPMIPA UPI	PM _{1.0}	27.86578	26	0	114	62.731212
	PM ₁₀	38.958778	36	0	158	36.533838
	PM _{2.5}	34.720305	32	0	140	71.995907
	CO	21.013901	20.22299	0.021481	127.0168	364.015108

The field test results show that the air quality across the four locations was accurately recorded. Based on Table 11, the data shows that the air quality in Bandung City, represented by the four points, falls into the Unhealthy to Hazardous categories. The locations with the highest concentrations based on the mean and maximum values are located in Location 2 and Location 4. Location 2 represents an area with dense traffic, covering a main road with heavy traffic flow. In contrast, Location 4 is an area representing offices that are not directly affected by public transport. These two areas are indicated to have Air Pollution Standard Index (ISPU) values categorized as Very Unhealthy (Location 2) and Hazardous (Location 4) based on the ISPU values.

Furthermore, another assessment is proven by the average concentration of the PM_{1.0} pollutant being above 20 µg/m³. A higher value for pollutant types with a small diameter indicates that the air quality around that location is more hazardous. Location 2 has an average PM_{1.0} value of 25 µg/m³, and Location 4 has an average PM_{1.0} value of 27 µg/m³. It can therefore be concluded that the Cileunyi location has a Very Unhealthy air quality, which can cause adverse health effects to a number of the population in this area. The air quality in Bandung is further exacerbated by the quality in the office area around the FPMIPA UPI Campus location, which has a Hazardous air quality level that can harm the population's health, causing symptoms such as eye irritation, coughing, and sore throat. There are several possibilities that contribute to the high ISPU values at these two points. The spot at Location 2 in the Cileunyi area is highly vulnerable to increasing pollution levels because the sensor is positioned across from the Cileunyi main road, where many motor vehicles pass by in that area. Additionally, the sensor placed at Location 4 in the office area of the FPMIPA A UPI Lecture Building is close to a waste burning site originating from that building.

On the other hand, the data retrieved from Location 1 and Location 3 can be categorized as having Unhealthy air quality with ISPU values ranging from 105 to 120. This signifies that the air quality is detrimental to health for humans, animals, and plants, as well as to the environmental aesthetic. The ISPU figures in these locations are not as high as those in Location 2 and Location 4, likely because these locations are not frequently passed through by vehicles and are not main roads. Furthermore, the sensor storage points at these locations still have many tall trees, which can absorb air pollutant particles such as dust and harmful gases, and can also help cleanse the surrounding air.

Choropleth Map of Air Pollution (ISPU Mean)

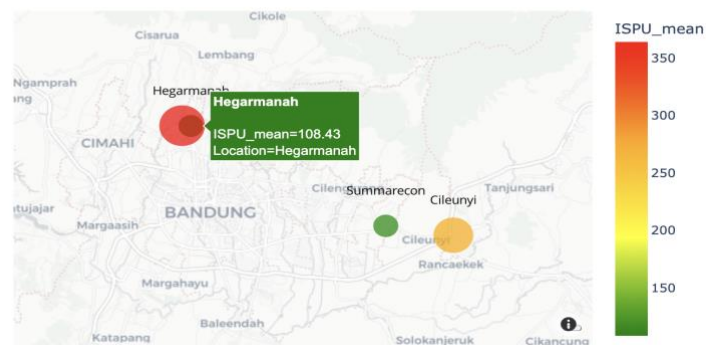


Figure 5. Choropleth map of air pollution (ISPU Mean)

Stacked Bar Chart - Average Pollutant Concentration per Location

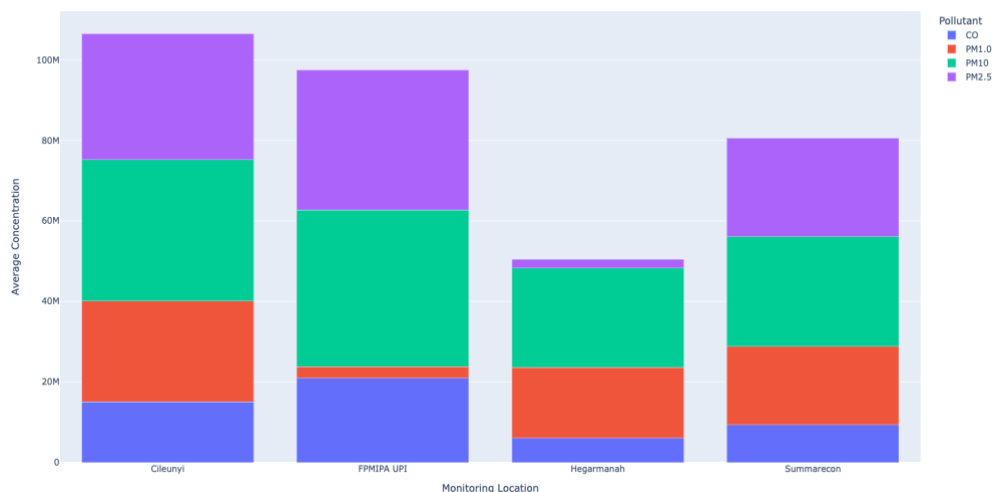


Figure 6. Average Pollutant Concentration per Location

3.6. Temporal Analysis

The temporal analysis conducted in this study used a time-series analysis method, which aims to analyze trends, seasonality, and fluctuations in pollution levels. For this purpose, the analysis was conducted by understanding how the pattern of air quality varies between weekdays and weekends. Analyzing this pattern is important because human activities, such as vehicular traffic and industrial operations, tend to be more intensive on weekdays, which can affect air pollution levels. This analysis also provides deeper insight into when and where preventive measures are more necessary, and how these results can be applied to improve the quality of life for the community around the monitoring locations. The following is a comparison of all pollutants (PM_{1.0}, PM_{2.5}, PM₁₀, and CO) from the four locations during the monitoring period, comparing weekdays (Monday - Friday) and weekends (Saturday - Sunday).

Table 12. Actual Measurement Result on All Four Locations Based on Day Type

Content	Day Type	PM _{1.0}	PM ₁₀	PM _{2.5}	CO
Hegarmanah	Weekday	16.91722851	23.70869938	21.33278852	5.885644407
	Weekend	19.15529032	26.81694422	24.06233774	6.315864379
Cileunyi	Weekday	24.19994593	33.93231292	30.24026467	15.18591963
	Weekend	27.10357143	38.0011378	33.79067636	14.78374427
Summarecon	Weekday	18.92428296	26.56562058	23.80156913	9.389892698
	Weekend	20.75618921	29.09312239	26.01547303	9.30617791
FPMIPA UPI	Weekday	27.01357763	37.7768306	33.6750884	21.02943954
	Weekend	29.95795455	41.8604798	37.28633207	20.97575511

Based on the air quality analysis concerning the temporal factor on weekdays and weekends, as explained in Table 12 and Figures 7-10, an increase is shown during the weekend. Every pollutant particle element assessed demonstrates a rise during that time. For example, the PM_{1.0}, PM₁₀, PM_{2.5}, and CO particles increased by 1-2% compared to the amount on weekdays. This may indicate a potential increase in motor vehicle fuel emissions, which is caused by heavy traffic and a rise in the number of motor vehicles. Furthermore, it may also occur due to open burning activities such as waste incineration, or the use of household appliances such as gas stoves, or due to cigarette smoke.

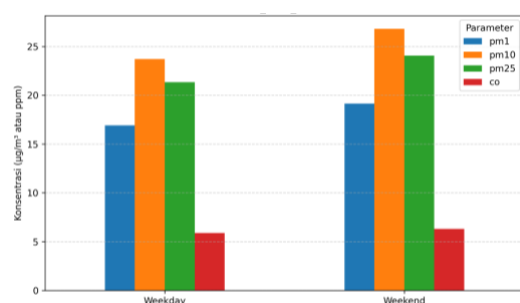


Figure 7. Temporal Analysis of Location 1

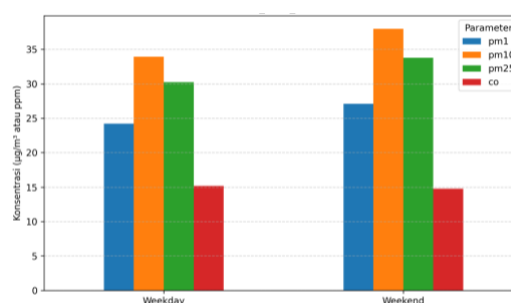


Figure 8. Temporal Analysis of Location 2

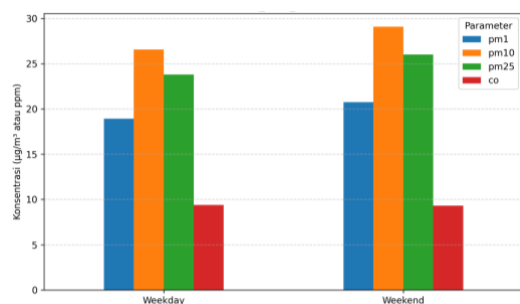


Figure 9. Temporal Analysis of Location 3

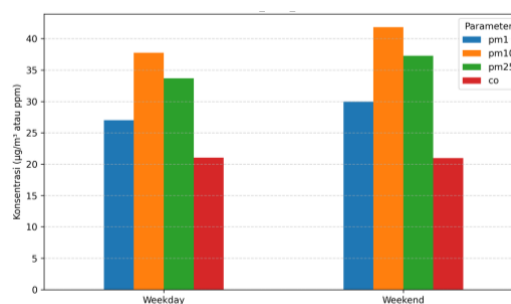


Figure 10. Temporal Analysis of Location 4

Based on the analysis of Figure 7 and Figure 10, it is concluded that the pattern of average concentration from Location 1 to Location 4 is exactly the same. The pollutants PM_{1.0}, PM_{2.5}, PM₁₀, and CO have higher values on weekends, and this may be caused by increased traffic volume compared to weekdays, especially at Location 2, which is a major road or highway. If the highest particle concentration is observed to be PM₁₀, it indicates that the air quality in Bandung City is largely sourced from road dust, construction, open burning, or industrial activities.

In addition, this study conducted a time series analysis by predicting pollutant levels for the next 7 days based on the last 3 months of data from 4 locations using LSTM and GRU that illustrate at Figure 11-14.

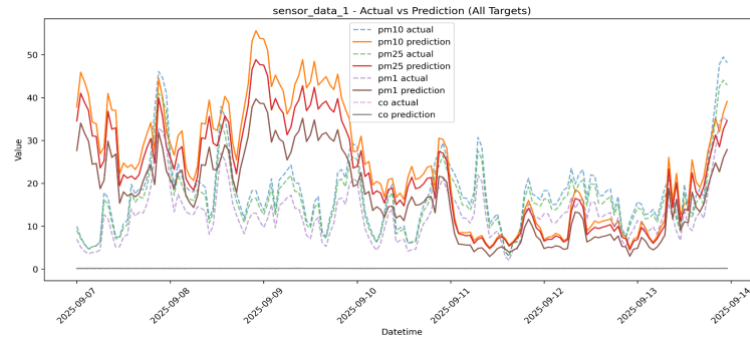


Figure 11. Trend analysis of actual and predicted pollutant concentrations in Hegarmanah, Bandung

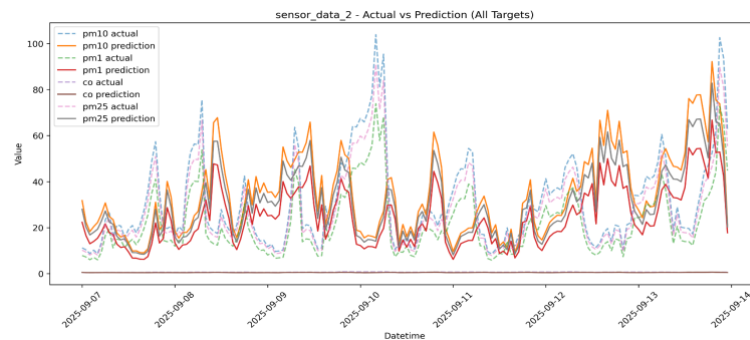


Figure 12. Trend analysis of actual and predicted pollutant concentrations in Cileunyi, Bandung

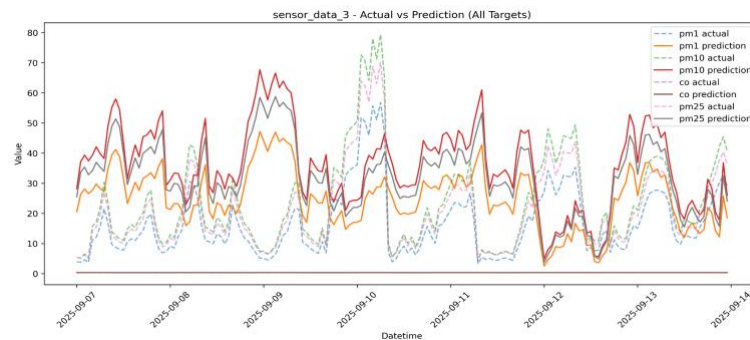


Figure 13. Trend analysis of actual and predicted pollutant concentrations in Summarecon, Bandung

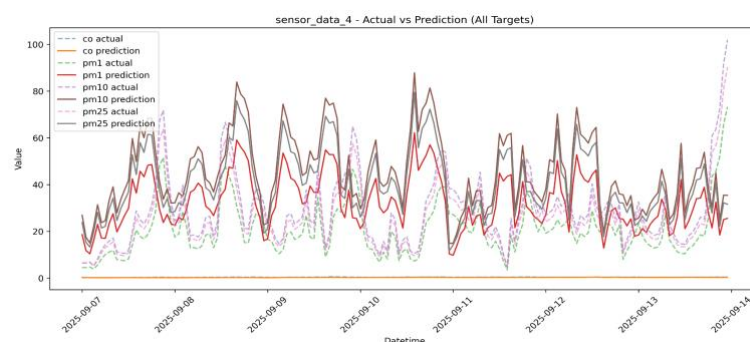


Figure 14. Trend analysis of actual and predicted pollutant concentrations in FPMIPA UPI, Bandung

The line graph illustrates the comparison between the actual and predicted air pollution data recorded by *sensor_data_1* (Figure 11), *sensor_data_2* (Figure 12), *sensor_data_3* (Figure 13), and *sensor_data_4* (Figure 14) from September 7 to September 14, 2025. It includes four pollutants: PM_{1.0}, PM₁₀, PM_{2.5}, and CO (carbon monoxide). Each pollutant is represented by two lines, where the dashed lines indicate the actual measured values, and the solid lines represent the predicted values generated

by the machine learning model. Overall, the predicted data closely follow the trend of the actual data, suggesting that the model effectively captures the temporal variation in air pollution levels. The results show that $PM_{1.0}$ and PM_{10} exhibit strong periodic fluctuations with predictions aligning well with the observed peaks and troughs. $PM_{2.5}$ also demonstrates a similar trend, reflecting the model's ability to adapt to short-term changes in concentration. Meanwhile, CO levels remain relatively stable at lower concentrations, indicating less variation during the observation period. Although minor deviations occur between actual and predicted values particularly at the peak pollution moments the general similarity of patterns indicates that the prediction model using LSTM and GRU methods, performs effectively in forecasting air quality conditions in the monitored area.

4. CONCLUSION

The Internet of Things based system successfully monitored real-time air quality across multiple zones in Bandung. This approach generated a comprehensive spatiotemporal analysis by integrating both particulate matter and gas pollutants (CO). Based on the analysis of air pollution in Bandung City, derived from sensor storage points at four locations: the office area, residential area, densely populated area, and main road/highway, the predominantly air quality in Bandung City is categorized as unhealthy with ISPU values exceeding 100. This is indicated by the high levels of CO and fine particulate matter ($PM_{1.0}$, $PM_{2.5}$, PM_{10}), which are key indicators of declining air quality in the monitored region. CO levels exhibit the highest Air Pollution Standard Index (ISPU) value across all areas, where the PM value increases along with the increase in CO value. The rise in these pollutant levels is observed to increase during the weekend, indicating a surge in emission combustion from motor vehicles due to increased resident activity on the weekend.

Meanwhile, the prediction of air pollution quality data was successfully monitored based on the integration of the monitoring system with the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) machine learning models. The prediction results from both models show comparable performance. The experiment shows that the GRU model achieves an average RMSE of 2.2279405 and an average MSE of 7.236050563. Compared with the LSTM model, GRU reduces the average RMSE by 0.456741375 and the average MSE by 3.653713747, indicating a consistent, though modest, improvement in prediction accuracy. However, based on the average across each sensor, the GRU model consistently yields lower RMSE and MSE values compared to the LSTM model. This demonstrates that the overall performance of the GRU model is superior to that of LSTM, making GRU more highly recommended for use in the prediction process. Further research could explore spatiotemporal models that capture relationships between monitoring locations, assess prediction uncertainty, and test model performance at previously unseen sites.

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