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Universitas Siber Asia

ISIBER International Seminar on Intelligent Business and Edge-Computing Research

IEEE Indonesia Section

PROCEEDING

ISIBER

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Welcome Speech from Rector

Good morning, and may peace be upon us all.

The honourable,

- Representative from the IEEE Indonesia Section, as the co-sponsor of this event,
- Our esteemed Plenary Speakers,
- The General Chair of ISIBER 2026, along with the entire Steering and Organizing Committees,
- And all the distinguished researchers, academicians, and professionals participating today.

First of all, I would like to welcome you and express my highest congratulations on the opening of ISIBER. We are exceptionally proud to host this momentous event today, on February 26, 2026. For this inaugural edition, it is a tremendous achievement that the accepted and presented papers will be submitted for inclusion in a globally recognized IEEE proceeding. Congratulations to all the authors and the organizing team for this excellent milestone.

However, as an institution that constantly innovates, our vision must not stop here. It is my great hope that the academic spirit born from the discussions at ISIBER today does not end with the conference proceedings. Moving forward, I have a strong ambition to develop these high-quality research collections into a regular academic journal publication. We believe that having a reputable, periodic journal will further drive continuous research and technological improvements in the future.

To achieve this, we cannot do it alone. As Universitas Siber Asia continues to advance our grand vision to become a leading cyber university in Southeast Asia, we recognize the vital importance of collaboration. Therefore, my message to you today is simple: let's continue to work together. I invite everyone to strengthen your partnerships with Universitas Siber Asia. Let us create a strong synergy to answer the various theoretical and practical challenges in this digital era.

Finally, I wish you all a highly productive, inspiring, and successful conference. May this event spark new ideas and bring real benefits to our society.

Thank you very much

Jang Youn Cho, B.A., M.PA., Ph.D., C.PA.

Rector of Asia Cyber University

Welcome Speech from Chair

Distinguished speakers, respected researchers, participants, ladies and gentlemen,

On behalf of the Organizing Committee, it is my great honor to welcome you to the **2026 International Seminar on Intelligent Business and Edge-Computing Research (ISIBER)**, hosted by Universitas Siber Asia in Jakarta, Indonesia. We are truly grateful for your presence and participation. Your contributions as authors, presenters, reviewers, and attendees are the foundation of this conference's success.

This conference is particularly significant as it is held in collaboration with the IEEE Indonesia Section. As a globally respected professional organization, IEEE upholds rigorous academic and ethical standards. Our

partnership means that every submitted paper undergoes a rigorous peer-review process to ensure quality, originality, and relevance.

ISIBER 2026 received 586 paper submissions from 33 countries. This remarkable number reflects the growing international recognition of our conference. However, due to the stringent selection criteria, **only 30,72%** of the submissions were accepted, representing authors from **20 countries**. The review process was highly competitive, and we sincerely appreciate the dedication of our reviewers and technical committee members for maintaining fairness and excellence.

As General Chair of the Organizing Committee, I would also like to apologize for any shortcomings during this event. We remain committed to continuous improvement and welcome your feedback.

Finally, we hope this conference fosters insightful discussions, meaningful collaborations, and lasting professional connections. Thank you once again for being part of ISIBER. We are truly honored by your presence and participation. On behalf of the entire organizing committee, I wish you a productive, enriching, and memorable conference experience.

We sincerely hope to welcome you again at the next edition of the ISIBER conference next year. Until we meet again, please stay safe, stay inspired, and continue contributing to the advancement of knowledge in our global community.

Thank you very much.
Chair,

Dr. Ucuk Darusalam, S.T., M.T

Foreword

In an era defined by unprecedented data generation and the relentless pursuit of immediacy, the convergence of intelligent business practices with edge-computing research represents one of the most transformative movements in modern technology. As we stand at the intersection of artificial intelligence and distributed systems, it becomes increasingly clear that the future of digital infrastructure lies not solely in centralized cloud architectures, but in the ability to process, analyze, and act upon data at its very source. This foreword introduces a collection of thoughts and scholarly contributions that explore this dynamic frontier.

The synergy between intelligent business and edge computing creates remarkable opportunities for innovation across industries. By pushing computational intelligence closer to where data originates, organizations can achieve real-time insights, enhanced security, reduced latency, and more efficient resource utilization. From smart manufacturing floors that adapt instantaneously to changing conditions, to retail environments that personalize customer experiences through edge-based analytics, the applications are as diverse as they are profound. This research domain challenges us to rethink traditional models of information processing and to imagine new architectures that are both resilient and responsive.

We extend our sincere appreciation to the researchers, practitioners, and thought leaders who have contributed their insights to this important discourse. Their work illuminates the path forward, addressing critical questions about scalability, interoperability, and the harmonious integration of intelligent algorithms within edge environments. These collected works will inspire continued exploration, foster meaningful collaborations, and ultimately accelerate the responsible adoption of intelligent edge technologies across the global business landscape. Welcome to this intellectual journey at the forefront of computing innovation.

Guest Editor

Ferry Wahyu Wibowo

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B TOP 3 5 A B C D E F G H I J K L M N O P Q R S T U V

C TOP 3 5 A B C D E F G H I J K L M N O P Q R S T U V

Closed-Loop Controlled Soft Robotic Sleeve with Programmable Pressure Profiles for Compression Therapy

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Comparative Analysis of Machine Learning Regression Models for Stock Price Prediction Using Financial Ratios on the Indonesian Stock Exchange

Comparative Analysis of MobileNet Architectures for Apple Disease Classification

Comparative Analysis of VGG16, ResNet50, and MobileNetV2 Convolutional Neural Networks for Clothing Recognition

Comparative Analysis of YOLO Algorithm Performance in Firearm Detection on Static Images

Comparative Study of CNN Architectures: VGG16, ResNet50, and MobileNetV2 in Flower Image Classification

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Comparison of Multi-Layer Perceptron and XGBoost for Urgency Classification of Student Complaints Using IndoBERT Embeddings

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Short-Term Hyperlocal PM2.5 Forecasting Based on Meteorological Conditions Using GRU Architecture

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***Abstract*—Particulate matter 2.5 (PM2.5) is the most dangerous air pollution contributor. In heavily affected cities like Jakarta, the effectiveness of public health measures is hindered by information delays. This study addresses this gap by developing a short-term, hyperlocal PM2.5 forecasting model using a GRU architecture. The model was trained and evaluated on 3 years of hourly PM2.5 and meteorological data from Grogol Petamburan, West Jakarta. The study compared three scenarios at 1, 3, and 6-hour forecast horizons: a full model with all meteorological features, an ablation model excluding planetary boundary layer and solar radiation, and a univariate baseline using only PM2.5 data. The best evaluation for the full model is at the 1-hour prediction horizon, with an RMSE value of 8.00, MAE of 5.27, and MAPE of 11.24%. The results demonstrated that while 1-hour forecasts are dominated by PM2.5 autocorrelation, the inclusion of meteorological data is crucial and significantly improves accuracy for 3-hour and 6-hour predictions. The most significant finding was that the ablation model consistently outperformed the full model across all horizons and error metrics. An apparent paradox arose as feature importance analysis identified solar radiation as the most critical predictor. This was resolved by the fact that planetary boundary layer feature was found to be detrimental, adding noise, and the information from solar radiation was found to be redundant due to high multicollinearity with temperature and humidity. The study concludes that a more parsimonious model, leveraging careful feature selection, is both more computationally efficient and more accurate.**

***Index Terms*—PM2.5, meteorology, GRU, short-term, hyperlocal.**

I. Introduction

Air pollution ranks among the deadliest threats to global health, claiming 8.1 million lives in 2021 alone. Particulate matter 2.5 (PM2.5), airborne particles with a diameter of less than 2.5 micrometers, is the most dangerous pollutant and a major contributor to this disease burden [1]. In Indonesia, this issue is particularly relevant, as Jakarta is consistently ranked among the world's most polluted cities [2], [3]. High PM2.5 levels in Jakarta have been linked to thousands of cases of heart and respiratory diseases and billions of dollars in economic losses annually [4].

The main gap in addressing this issue is the delay in information. Existing air quality monitoring stations tend to function as historical measurements, not predictive tools. This delay makes the available data less relevant to the public for effective preventive measures [5].

This problem is exacerbated by the highly dynamic and hyperlocal nature of PM2.5 pollution. Concentrations can fluctuate significantly within a few city blocks or over hours due to differences in local emission sources and changing meteorological conditions [6], [7], [8]. Therefore, citywide and daily forecasts are insufficient to provide accurate warnings.

To address this gap, this study develops a PM2.5 forecasting model focused on short-term, hyperlocal forecasting. The model uses a deep learning approach that excels at modeling complex nonlinear time-series patterns [9], [10], [11]. Specifically, it implements a gated recurrent unit (GRU) architecture, which efficiently and robustly handles sequential data [12].

Several related studies inspired this research, i.e., Ratchagit [20] showed that a hybrid model with optimized weights can improve prediction accuracy compared to a single model. Handhayani [21] identified causal relationships between variables and concluded that an LSTM (Long short-term memory) model with integrated data provided the best predictions. Halim *et al.* [22] concluded that GRU can predict most pollutants well.

The main contributions of this research are as follows:

- Implementation of GRU architecture for short-term PM2.5 prediction using exogenous data at the hyperlocal scale.
- Evaluation of model performance at 3 different prediction time horizons (1, 3, and 6 hours).
- Comparative analysis of the impact of adding planetary boundary layer and solar radiation meteorological features on model accuracy.

II. Methods

This study follows the cross-industry standard process for data mining (CRISP-DM) data mining workflow, the standard approach for data science projects [13]. CRISP-DM consists of several stages (see Fig. 1).

A. Data Understanding

The prediction model uses two time-series datasets: PM2.5 and meteorological data. Both datasets are measured in their native units and presented on an hourly basis. The data span 3 years, from August 4, 2022, to August 3, 2025, and include 26,305 rows. Both datasets are from the same location

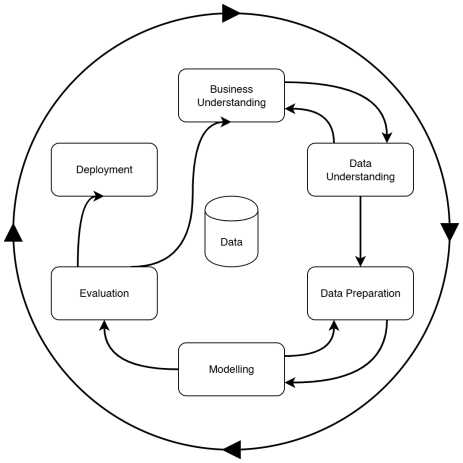

Fig. 1. Workflow of CRISP-DM Methodology.

in Grogol Petamburan, West Jakarta. The data come from Open-Meteo (https://open-meteo.com), a weather API freely available for non-commercial use. PM2.5 data is the input and output for predictions. The meteorological data contains 9 features and is used solely as input. Table I explains the data features; Table II shows sample data from a few features.

TABLE I
DATA FEATURES

No	Feature Name	Description
1	Timestamp	Information on the date, month, year, and time of data recording.
2	Temperature	The air temperature at a height of 2 meters above ground level, measured in degrees Celsius (°C).
3	Wind speed	Wind speed at a height of 10 meters above ground level, measured in kilometers per hour (km/h).
4	Wind direction	The wind's origin direction at a height of 10 meters above ground level, measured in degrees (from 0° to 360°). 0° indicates a wind from the north, 90° from the east, 180° from the south, and 270° from the west.
5	Precipitation	The amount of accumulated rainfall, measured in millimeters (mm).
6	Humidity	Relative humidity at a height of 2 meters above ground level, measured as a percentage (%). A value of 100% means the air is saturated with water vapor.
7	Air pressure	Atmospheric pressure at ground level, measured in hectopascals (hPa).
8	Planetary boundary layer	The height of the lowest atmospheric layer that is directly affected by activity on the ground surface, measured in meters (m).
9	Solar radiation	The amount of solar radiation received by the ground surface is measured in watts per square meter (W/m^2).
10	PM2.5	PM2.5 values, measured in micrometers per cubic meter ($\mu m/m^3$).

To understand the interrelationships between the predictive features and the target variable, a Pearson correlation matrix was computed, as shown in Fig. 2. This preliminary analysis provides critical insights into the dataset's characteristics.

TABLE II
SAMPLE DATA

Time	PM25	Tem	Hum	Pre	AP	WS
2022-08-04 00:00:00	94.3	24.5	95	0.0	1009.7	4.0
2022-08-04 01:00:00	108.3	26.0	86	0.0	1010.6	1.8
2022-08-04 02:00:00	99.7	27.5	78	0.0	1010.8	2.5
2022-08-04 03:00:00	101.3	28.9	72	0.0	1010.9	5.5
2022-08-04 04:00:00	84.1	29.7	69	0.0	1010.2	7.1

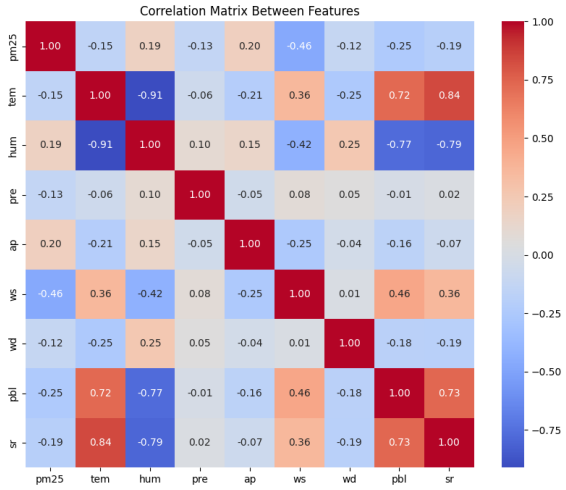

Fig. 2. Correlation Matrix Between Features.

The analysis first reveals the direct linear relationships with PM2.5. The most significant correlation is with wind speed, which has a moderate negative coefficient of -0.46. This aligns with physical expectations: higher wind speeds typically enhance pollutant dispersion, resulting in lower PM2.5 concentrations. Other notable, albeit weaker, correlations include air pressure at +0.20, suggesting that stable, high-pressure systems may trap pollutants, and PBL (planetary boundary layer) height at -0.25, indicating that a shallower boundary layer can concentrate pollutants. Precipitation also shows a slight negative correlation of -0.13, likely due to the washout effect.

A more prominent finding is the high degree of multicollinearity among the meteorological features, particularly those related to the diurnal cycle. There is a very strong positive correlation between temperature and solar radiation at +0.84, as solar radiation is the primary driver of surface temperature. Consequently, both tem and sr are very strongly and negatively correlated with relative humidity, at -0.91 and -0.79, respectively, as warmer air can hold more moisture.

The planetary boundary layer is also deeply intertwined with this diurnal cluster. It shows a strong positive correlation with solar radiation, at +0.73. Interestingly, the planetary boundary layer shows strong negative correlations with temperature

at -0.72 and humidity at -0.77. This complex, non-linear relationship among temperature, solar radiation, and planetary boundary layer highlights the challenge for the predictive model. This high redundancy also suggests that the information provided by solar radiation and the planetary boundary layer might already be implicitly captured by temperature and humidity, providing an early justification for the ablation study conducted later in this paper.

B. Data Preparation

Data preparation involves creating the final model input from raw data. This is done several times, based on data and model needs, without a fixed order. Steps include data cleaning and transformation. The two datasets are joined with a consistent time index. Data is then checked for missing values and duplicates. Missing values are filled by linear interpolation. Data is normalized for model balance.

Linear interpolation estimates the value of a feature between two known data points. This method connects the two points with a straight line. Its primary use is to estimate intermediate values, assuming the change is linear or can be approximated by a straight line [14]. This makes it a quick and easy way to fill in missing data or make simple predictions. The formula for linear interpolation is in Eq. (1).

$$y = y_1 + (x - x_1) \times \frac{(y_2 - y_1)}{(x_2 - x_1)} \tag{1}$$

Where:
y = Value that want to be searched
x = y position
x_1 = x value of the first known point
y_1 = y value of the first known point
x_2 = x value of the second known point
y_2 = y value of the second known point

Normalization is a method for rescaling data to a specific range, in this case, 0 to 1. Each feature value is transformed so the column's minimum becomes 0 and its maximum becomes 1. Values between the minimum and maximum are proportionally transformed into the new range [15]. The normalization formula is shown in Eq.(2).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

Where:
X_{norm} = Value after normalization
X = Original value
X_{min} = Minimum value of all data
X_{max} = Maximum value of all data

C. Modelling

The chosen model implements the GRU architecture. This deep learning method is good at capturing nonlinear patterns, works well with sequential data, and needs fewer computing resources. Efficient computing speeds up the training process. Model parameters are adjusted for better results, and the best models are saved for evaluation and deployment. GRU architecture consists of 4 concepts: update gate, reset gate, candidate hidden state, and hidden state [16]. The formula for each of those concepts is shown in order from Eq. (3-6).

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{3}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{4}$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{5}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{6}$$

Where:
z_t = Update gate
r_t = Reset gate
$\tilde{h}_t$ = Candidate hidden state
h_t = Hidden state
t = Time step at t
$x_{(t)}$ = Input value
$h_{(t-1)}$ = Memory from previous t
W and U = Weight value
b = Bias value

D. Evaluation

Three evaluation metrics are used to assess the performance of the GRU model: root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). In addition, the permutation feature importance (PFI) method is used to assess each feature's contribution to prediction and identify the most influential features.

RMSE is an evaluation metric that quantifies a model's prediction error by giving greater weight to larger errors. This is achieved by calculating the square root mean, which severely penalizes the model for even small errors. RMSE is a commonly used evaluation metric for regression problems [16], [17]. The RMSE formula is shown in Eq. (7).

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

MAE tells how far predictions are from actual values on average. The result uses the same units as the data, making it easy to understand. A score of 0 means perfect accuracy. Higher scores indicate a greater error rate [17]. The MAE formula is shown in Eq. (8).

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

MAPE is defined as the mean absolute percentage error, indicating how far off the model's predictions are in percentage terms. The advantage of MAPE is that its value is expressed

as percentages rather than data units, making it very easy to understand, even for non-technical users [18]. The MAPE formula is shown in Eq. (9).

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{9}$$

The evaluation metrics have the same variables used for all three, where:
n = Number of value points
i = Iteration at i
y_i = Actual value
$\hat{y}_i$ = Predicted value

PFI is a method for assessing a feature's importance by analyzing the model's prediction error after permuting the feature values, thereby breaking the relationship between the feature and the actual outcome. A feature is considered important if the randomized value increases the model error, meaning the model relies on that feature for predictions. Conversely, a feature is considered unimportant if the randomized value does not change the model error, meaning the model ignores that feature when generating predictions [19].

III. Results and Discussion

We used Python on Google Colab to model the entire process. To evaluate the proposed GRU model's performance in short-term, hyperlocal PM2.5 forecasting, a comprehensive comparative analysis was completed. The study used three experimental scenarios. These include a full model with all historical PM2.5 and meteorological data, including planetary boundary layer and solar radiation; an ablation model without planetary boundary layer and solar radiation; and a univariate forecast baseline using only historical PM2.5 data. Table III presented the consolidated results of this evaluation.

TABLE III
Evaluation

Scenario	Horizon	RMSE	MAE	MAPE
With planetary boundary layer and solar radiation	1 hour	8.00	5.27	11.24%
	3 hour	14.85	10.79	24.07%
	6 hour	19.30	14.72	33.11%
Without planetary boundary layer and solar radiation	1 hour	7.89	5.21	11.08%
	3 hour	14.65	10.62	23.62%
	6 hour	19.19	14.49	32.69%
Using PM2.5 only	1 hour	8.22	5.26	11.00%
	3 hour	15.58	11.48	25.81%
	6 hour	20.25	15.74	36.90%

A primary observation, consistent across all three scenarios, is the degradation of model performance as the forecasting horizon extends. As shown, all error metrics increase uniformly as the prediction time increases from 1 hour to 3 hours and then to 6 hours. For instance, in the 2nd scenario, the MAPE increases from 11.08% for the 1-hour forecast to 23.62% for the 3-hour forecast and finally to 32.69% for the 6-hour forecast. This trend is expected and highlights the inherent difficulty in time-series forecasting; uncertainty and predictive error naturally accumulate as the model attempts to predict further into the future.

The value of the exogenous feature becomes clear, especially at longer time horizons. The performance of these 3 models is very competitive. The baseline model in the 3rd scenario achieved a MAPE of 11.00%, slightly better than those in the 1st (11.24%) and 2nd (11.08%) scenarios. This indicates that, for short-term predictions (1 hour), PM2.5 autocorrelation is the most dominant predictive factor. The benefits of using meteorological data are significant. At a 6-hour time horizon, the baseline model's MAPE reaches 36.90%. In contrast, the first and second scenarios achieve significantly lower MAPEs of 33.11% and 32.69%, respectively. This indicates that as the forecast time horizon lengthens, the influence of PM2.5 history itself diminishes. The predictive power of meteorological variables becomes crucial for accurately capturing pollutant formation, dispersion, and transport.

Perhaps the most interesting finding of this evaluation is the result of the ablation study comparing the 1st and 2nd scenarios. The model excluding the planetary boundary layer and solar radiation consistently outperformed the full model across all three forecasting horizons and all three error metrics. For example, at the 3-hour horizon, the 2nd scenario achieved an RMSE of 14.65 and a MAPE of 23.62%, while the full model yielded a slightly higher RMSE of 14.85 and a MAPE of 24.07%. Although the performance difference is marginal, it is consistent. This result suggests that, within the specific GRU architecture and for this hyperlocal dataset, planetary boundary layer and solar radiation did not provide additional useful predictive information. It is plausible that these variables introduce noise or that their effects are already implicitly captured by other highly correlated features. This finding underscores the importance of careful feature selection, as a more parsimonious model like that in the 2nd scenario not only performs better but is also more computationally efficient.

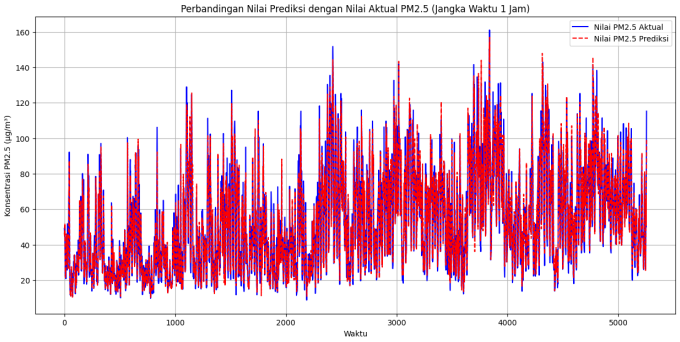

Fig. 3. Comparison of predicted with actual PM2.5 values (1-hour).

To visually assess the model's predictive capability, the actual versus predicted PM2.5 concentrations for the 1, 3, and 6-hour horizons are presented in Fig. 3-Fig. 5. Consistent with the error metrics in Table III, the 1-hour forecast shows the tightest alignment between the predicted values (red dashed line) and actual data (blue solid line). As the horizon extends to 3 and 6 hours, a gradual decoupling becomes apparent. While

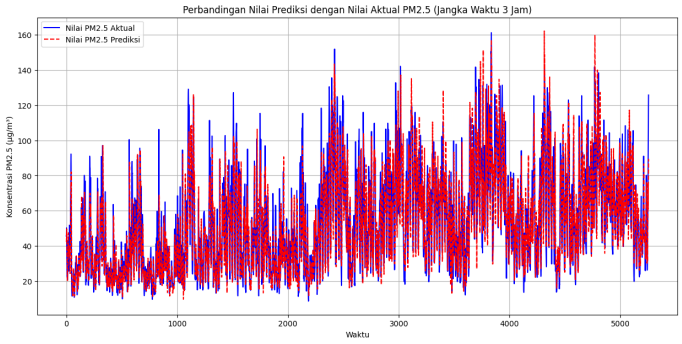

Fig. 4. Comparison of predicted with actual PM2.5 values (3-hour).

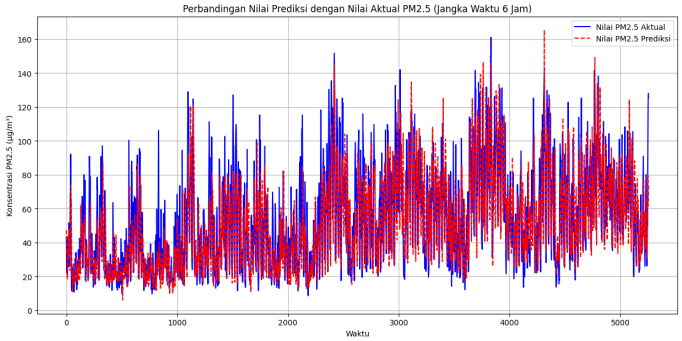

Fig. 5. Comparison of predicted with actual PM2.5 values (6-hour).

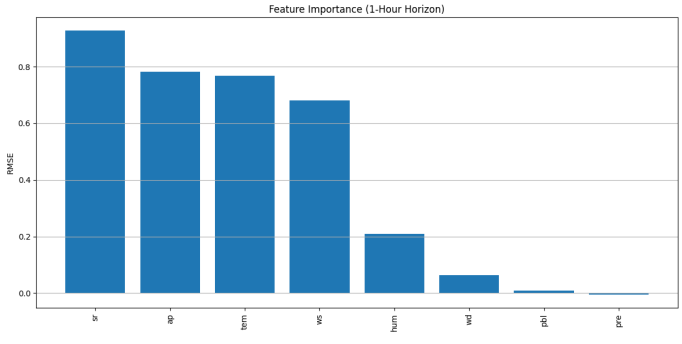

Fig. 6. Feature importance of 1-hour horizon forecast.

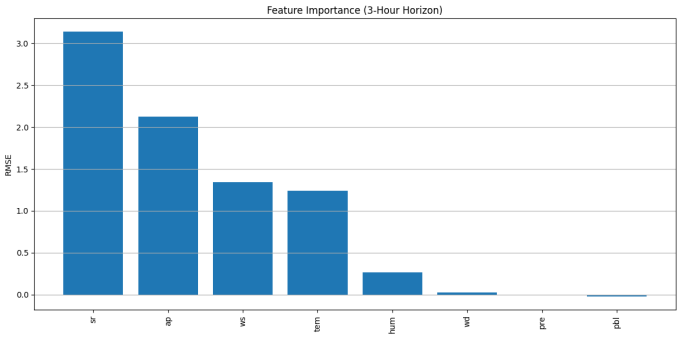

Fig. 7. Feature importance of 3-hour horizon forecast.

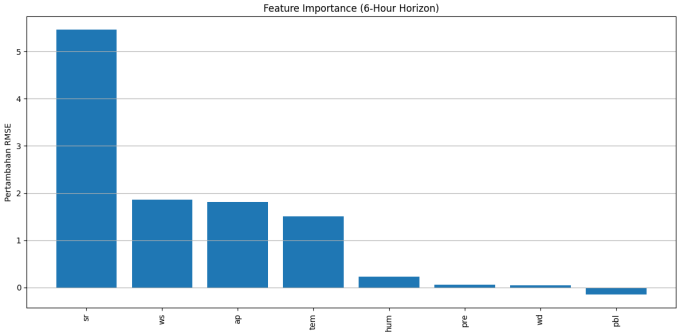

Fig. 8. Feature importance of 6-hour horizon forecast.

the model preserves the general trend, it struggles to capture extreme fluctuations accurately at the 6-hour mark, leading to the increased RMSE and MAPE observed previously.

To further deconstruct the model's behavior and understand the contribution of each meteorological variable, a feature importance analysis was performed. This research employed a permutation-based approach in which the value of a single feature is randomly shuffled, and the resulting increase in the model's RMSE is measured. A large increase in RMSE indicates that the model relies heavily on that feature for its predictions. This analysis was conducted for the full model at all three forecasting horizons. The results, presented in Fig. 6-Fig. 8, reveal several key insights.

Across all time horizons, 4 features consistently rank highest in importance: solar radiation, air pressure, temperature, and wind speed. The remaining features show significantly lower importance, and in some cases, negligible or negative importance. The relative importance of features changes with the forecast duration. Most notably, the importance of solar radiation dramatically increases as the horizon extends. In the 1-hour forecast, its RMSE is approximately 0.95, but it skyrockets to over 5.0 in the 6-hour forecast. This is logical, as solar radiation is a primary driver of the diurnal cycle, a pattern that strongly influences pollutant accumulation and dispersion over a 6-hour period. Similarly, wind speed shows a clear increase in importance at longer horizons, consistent with its role in pollutant transport and dispersion over time. Precipitation and planetary boundary layer consistently rank as the least important features. In the 3-hour and 6-hour forecasts, both features show a near-zero or negative importance. This implies that their inclusion not only fails to add predictive value but may also introduce noise, confusing the model and slightly degrading its performance.

However, the feature importance analysis presents an apparent paradox. The results from Table III indicated that the 2nd scenario performed better than the first. However, the feature importance charts clearly identify solar radiation as the single most important feature in the model. This seeming contradiction can be resolved by considering two factors: the detrimental effect of the planetary boundary layer and high multicollinearity. The feature importance charts strongly

confirm that PBL is not a useful predictor in this model. Its negative importance score at the 6-hour horizon suggests it is actively detrimental. Therefore, the performance gain observed in the 2nd scenario is, in part, achieved by simply removing this "noisy" feature.

The primary reason for the paradox is likely high multicollinearity between solar radiation and other features, particularly temperature and humidity. Solar radiation is the physical driver for temperature. In the first scenario, the GRU model, when given solar radiation, learns to rely heavily on it because it is a leading indicator. However, when it is removed, the model can still access much of the same information, which is already captured in the temperature and humidity variables. The ablation study in Table III suggests that the model trained in the 2nd scenario is slightly more robust and efficient. This implies that while solar radiation is informative, its information is redundant, and its direct inclusion might be less clean for the model than using its proxy variables alone.

IV. Conclusion

This study successfully developed and evaluated a GRU architecture for short-term, hyperlocal PM2.5 forecasting, specifically addressing the information delay gap that hinders effective public health warnings. The model, trained on three years of hourly data from Grogol Petamburan, West Jakarta, demonstrated its ability to capture the complex, non-linear patterns of pollutant behavior.

The evaluation confirmed that while 1-hour predictions are dominated by PM2.5's own autocorrelation, the inclusion of meteorological data is crucial for longer-term forecasts. At the 3-hour and 6-hour horizons, the GRU models incorporating exogenous features significantly outperformed the univariate baseline, demonstrating the value of meteorological data for predicting pollutant formation and dispersion. The most significant finding emerged from the ablation study. The model excluding planetary boundary layer height and solar radiation consistently achieved lower error rates than the full model across all metrics and horizons. This suggests that a more parsimonious model is not only more computationally efficient but also more accurate.

This apparent paradox, where feature importance analysis identified solar radiation as the most critical feature, yet its removal improved the model, was resolved by two key factors. First, the planetary boundary layer feature was found to be detrimental, introducing noise rather than predictive value. Second, the high multicollinearity between solar radiation, temperature, and humidity meant its information was redundant. The model could effectively leverage temperature and humidity as proxy variables, leading to a more robust and cleaner prediction. This research underscores the critical importance of careful feature selection, demonstrating that simply adding more data does not guarantee a better forecasting model.

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