

A Lightweight Machine Learning Framework for Urban Air Quality Prediction

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Abstract

This study proposes a lightweight machine learning framework for short-term forecasting of PM_{2.5} and PM₁₀ in Seoul, South Korea, using 2024 environmental data from 50 monitoring stations. This research compares a Random Forest regressor against a Linear Regression baseline. The Random Forest model outperformed the baseline model, achieving an R² of 0.832 and 0.827 for PM_{2.5} and PM₁₀, respectively. Importantly, the framework demonstrated excellent computational efficiency, with training times under a second and prediction execution by 39.67 milliseconds. These results justify deployment in cities with limited infrastructure.

Keywords: Random Forest, Linear Regression, PM_{2.5}, PM₁₀.

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1.0 Introduction

Air pollution is currently one of the most significant public and environmental health problems. Numerous studies have shown that short- and long-term exposure to air pollutants is associated with adverse health effects (Chen et al., 2008). Among the major pollutants, PM_{2.5} (particulate matter with an aerodynamic diameter of less than 2.5 µm) and PM₁₀ (particulate matter with an aerodynamic diameter of less than 10 µm) pose significant danger to human health. Since it is mostly absorbed through the respiratory system, it can enter the lungs and reach the bloodstream (Huang et al., 2023). According to recent studies, fine particulate matter or PM is responsible for 4 million deaths globally from illnesses such as respiratory infections, heart diseases, cancers, and other illnesses. (Thangavel et al., 2022). So, monitoring and predicting these pollutants have become a global health priority. However, due to the highly volatile nature of these data, short-term predictions are difficult and rare (Dong et al., 2024). Most existing systems use statistical methods, such as linear regression, which fail to handle these highly nonlinear pollution data (R. A. et al., 2025). This study aims to predict PM_{2.5} and PM₁₀ in Seoul using a machine learning framework with CO, NO₂, wind speed, and humidity as inputs. Here, two models are compared: Linear Regression as the baseline and Random Forest as the main model. The framework is designed for low-resource hardware that can be deployed to cities with limited infrastructure. Moreover, the resulting predictions can be turned into health advisories for locals and local governments. Section 2 describes the literature review. Section 3 explains the methodologies and system configuration, and parameters. Section 4 presents the findings after training the model; Section 5 provides a deep-dive discussion of the model's results; Section 6 summarizes and concludes the paper.

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2.0 Literature Review

Over the past decade, atmospheric pollutants forecasting has evolved significantly, going from deterministic physical models to data-driven computational approaches. Chemical transport models (CTMs) like CMAQ and WRF-Chem are highly accurate but computationally intensive and require extensive input data, making them impractical for deployment in resource-limited areas (Wang et al., 2025). Traditional and simpler statistical methods, such as Autoregressive Integrated Moving Average ARIMA and multiple linear regression, have been utilized as alternatives that work well with stationary data with regular patterns. However, they struggle with volatile urban air quality data (Cao et.al., 2024).

Recently, researchers have integrated deep learning techniques for advanced air quality prediction. Studies using Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) have achieved high accuracy in PM2.5 prediction. However, massive datasets, long training times, and expensive cloud servers are required to implement these deep learning models (Yan et al., 2021). For developing countries and local municipalities, this computation cost acts as a significant barrier.

To address these constraints, researchers have started using ensemble machine learning models such as Random Forest, an algorithm originally introduced by Leo Breiman and Adele Cutler in 2001 that builds multiple decision trees to reduce variance and control overfitting. This has proven highly effective for PM2.5 predictions without placing excessive computational burden on neural networks (Wang et al., 2019). Research by Jayamurugan et al. in 2013 shows that features such as wind speed and humidity significantly influence forecasts because wind affects the physical dispersion of particulates, and humidity affects atmospheric suspension. In Seoul, over the past 10 years, phenomena known as Yellow Sand from the Gobi Desert and Inner Mongolia have frequently occurred, causing severe PM10 spikes during spring. And a significant drop in particulate concentration during summer monsoon rain (Lee et.al., 2013). Despite advances in predictive tech, most high-performing systems depend on expensive infrastructure. This study addresses this gap by validating a Random Forest framework that achieves high accuracy on standard consumer-grade hardware, by optimizing precision and deployment feasibility.

3.0 Methodology

3.1 Data Source

The dataset used in this research was sourced from Seoul Open Data Plaza, an open-source portal for high-fidelity environmental monitoring data. The data consists of daily ambient air quality readings from 50 stations across the Seoul metropolitan area. These stations are strategically located to capture diverse microenvironments, including densely populated residential districts, heavily trafficked roadways, and preserved ecological areas, thereby providing a robust representation of the city's atmospheric profile. The dataset spans an entire year from January 1, 2024, to December 31, 2024, capturing a comprehensive annual climate variation. (Seoul Open Data Plaza. 2024)

The decision to use Seoul Open Data Plaza was made based on its reliability, broad temporal coverage, and public accessibility. These are aligned with the metrics we set to find a dataset that yields high-quality, low-noise variant data to generate objective features for our model framework. First, the contribution of 50 monitoring stations scattered across the metropolitan area is important for ensuring the model captures the full range of the city's air pollution levels. The dataset ensures that the model achieves a wide range of environmental outcomes, helping it generalize to other urbanized areas. Second, a full year of observation provides complete temporal resolution to record all movements in pollution levels and capture seasonal trends. A full annual exposure ensures the model encounters recurring phenomena. For example, heating emissions from mass traffic during congested hours under hot summer or dust events during the spring, and natural forest fire incidents. This guarantees temporal completeness, encouraging the model to work precisely and objectively throughout any given year.

3.2 Variables

The study consists of six primary variables. The input features include gaseous pollutants such as Nitrogen Dioxide (NO₂), Ozone (O₃), Carbon Monoxide (CO), and Sulfur Dioxide (SO₂). Additionally, humidity and wind speed data were acquired from the Open-Meteo weather archive. These meteorological inputs are used as supplementary environmental variables. The variables used for prediction are PM_{2.5} and PM₁₀. It is important to note that CO and NO₂ are used exclusively as predictive features, not as targets for study. (Open-Meteo 2024). The integration of these foundational datasets required a rigorous preprocessing pipeline to ensure temporal alignment between the hourly-calibrated atmospheric readings and the meteorological variables. By prioritizing feature importance analysis within our Random Forest architecture, we observed that the temporal lag—the pollutant concentrations from previous hours—functions as a high-impact predictor alongside wind speed. This methodological efficiency allows the model to capture the nonlinear

complexities of urban air sheds without the significant computational overhead typically associated with resource-intensive deep learning models. Furthermore, because the system uses consumer-grade hardware and maintains training times of under 1 second, it is a scalable blueprint for edge computing integration. Such rapid processing capabilities are essential for smart city initiatives, enabling well-timed health advisories that rely on real-time atmospheric intelligence rather than delayed, centralized modeling.

3.3 Data Preprocessing

Data integrity was maintained through multiple preprocessing protocols. Missing values accounted for 2% of the dataset and were imputed using the forward-fill method.

The formula is presented as follows (Lachin et.al. 2016):

$$\tilde{x}_t = \begin{cases} x_t, & \text{if } x_t \text{ is observed} \\ \tilde{x}_{t-1}, & \text{if } x_t \text{ is missing} \end{cases}$$

For a gap of missing values, this means every missing time point takes the most recent observed value. That is the same idea described in the LOCF literature: “a missing follow-up visit value is replaced by (imputed as) that subject’s previously observed value, that is, the last observation is carried forward.” “Missing values were imputed using forward fill, where each missing value was replaced by the most recent observed value.”

The final dataset comprised 18300 rows across the 50 stations. Min-Max normalization was applied to prevent variable scale from biasing the machine learning algorithms so that high-value features like humidity do not mathematically overpower low-value features like CO concentrations (Patro et.al., 2015).

3.4 Feature Engineering

To capture the volatile nature of air pollution, Lag-1 or previous day PM levels were generated for CO, NO₂, PM10, and PM2.5 to give the model immediate historical context.

3.5 Train/Test Split

The data was split into training from January 1 to October 14, 2024 (14,400 rows). The testing set was from October 15 to December 31, 2024 (3,900 rows). Making it about an 80/20 split. This was done to evaluate the framework’s true prediction capabilities and to simulate a real-world deployment scenario.

3.6 Models

Two predictive models, Linear Regression (Montgomery et.al., 2021)

whose formula is speculated below:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i$$

Where : y_i represents the prediction of the i th example of the dataset.

x_{ip} represents the p th feature of the i th example in a dataset.

β_p represents the p th weight corresponding to the same position feature, and

ε_i represents the bias of the i th example of the dataset.

and Random Forest (Breiman et.al., 2001). This model will take an ensemble of decision trees that are fed using a bootstrap-resampled dataset. The average is taken from the predictions of each decision tree and used as the final prediction. The formula is stated as below:

$$\hat{y} = \frac{1}{B} \sum_{b=1}^B T_b(x)$$

Where: \hat{y} is the average taken as the final decision

B is the number of decision trees inside the random forest.

b is the position of the decision tree inside the random forest.

$T_b(x)$ is the prediction made by the b^{th} decision tree.

Both were implemented via the Python Scikit-learn library (Pedregosa et al., 2011). Data manipulation and construction of lag features were done using the Pandas library (McKinney et al., 2010). The Random Forest was configured with 100 decision trees, a maximum depth of 8, and a minimum of 3 samples per leaf. These hyperparameters are selected to balance the complex interactions while controlling overfitting, sticking to the study's lightweight architecture requirement. All visualizations were generated using the matplotlib and seaborn libraries (Hunter et al. 2007).

3.7 Evaluation Metrics

The model was evaluated using three standard statistical metrics: Mean Absolute Error (MAE) to measure the average magnitude of errors in $\mu\text{g}/\text{m}^3$, Root Mean Squared Error (RMSE) to penalize outlier prediction errors, and the Coefficient of Determination (R2) for representing the proportion of variance in the target variables. Computational training and prediction times were recorded in milliseconds (ms) to validate the framework's low-resource deployment claims (Harishkumar et al., 2020).

4.0 Findings

4.1 Model Performance

Table 1. Random Forest and Linear Regression performances across all targets and metrics

(Source:) Created by the authors

Target	Model	MAE	RMSE	R2	Train_Time_sec	Prediction_Time_ms
PM2.5	Linear Regression	3.4527	4.5498	0.7082	0.009	0.33
PM2.5	Random Forest	2.538	3.4532	0.8319	0.609	39.67
PM10	Linear Regression	4.0439	5.549	0.8104	0.008	0.5
PM10	Random Forest	3.9173	5.3058	0.8266	0.609	40.98

As detailed in Table 1, for PM2.5, Random Forest got an R2 of 0.832 compared to the baseline's 0.708, representing a 17.5% improvement in explained variance. The improvement was further reflected in the error metrics, where RF got a highly precise MAE of $2.538 \mu\text{g}/\text{m}^3$ vs LR's $3.453 \mu\text{g}/\text{m}^3$. And in the case of PM10, RF achieved an R2 of 0.827, and LR got 0.810.

Actual vs Predicted — PM2.5 | Seoul Air Quality 2024

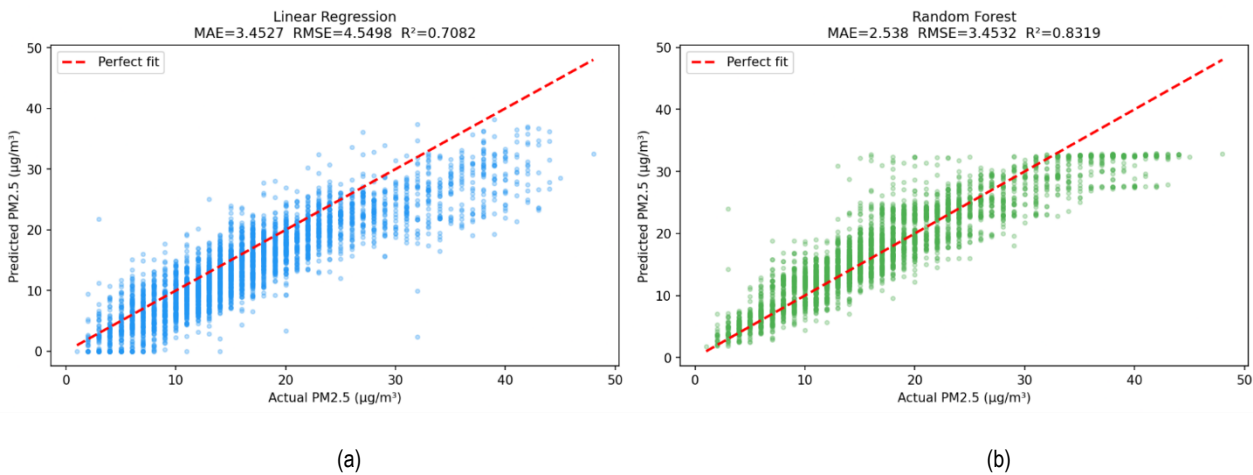


Fig. 1. (a) Linear Regression Actual vs Predicted PM2.5; (b) Random Forest Actual vs Predicted PM2.5

(Source:) Created by the authors

Fig. 1. a) and b) show that RF predictions are much more in line with the perfect-fit regression line, whereas LR is not as close.

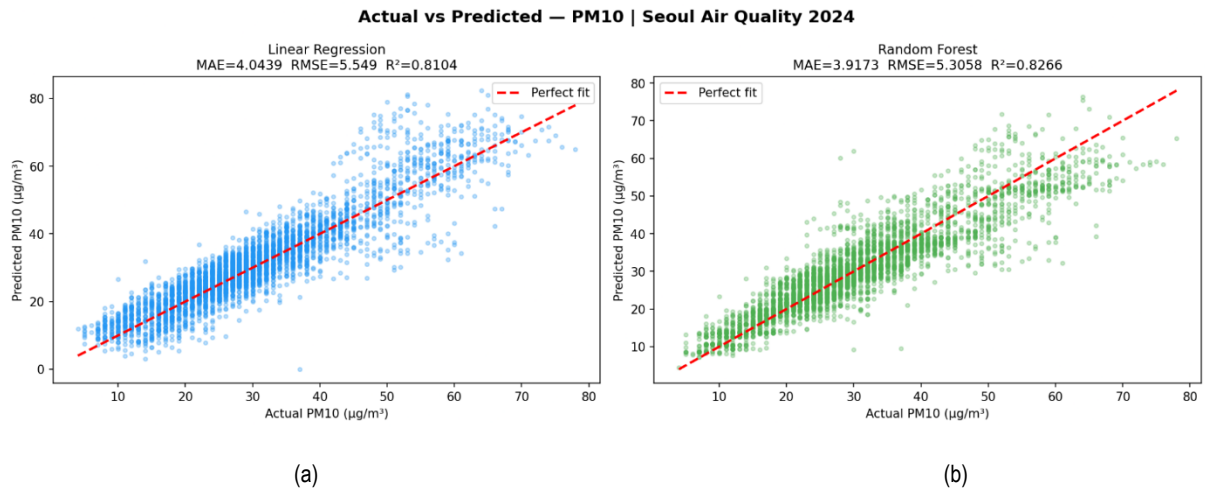


Fig. 2. a) Linear Regression Actual vs Predicted PM10; (b) Random Forest Actual vs Predicted PM10

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Fig. 2. a) and b) Similar to the previous one with PM2.5, these figures also show that RF is slightly ahead in terms of R2 of PM10. The computational evaluation showed the framework’s operational efficiency. While LR was trained in 0.009 seconds, the more complex RF model was trained in just 0.609 seconds and executed predictions in around 39.67 milliseconds on standard consumer hardware.

4.2 Feature Importance

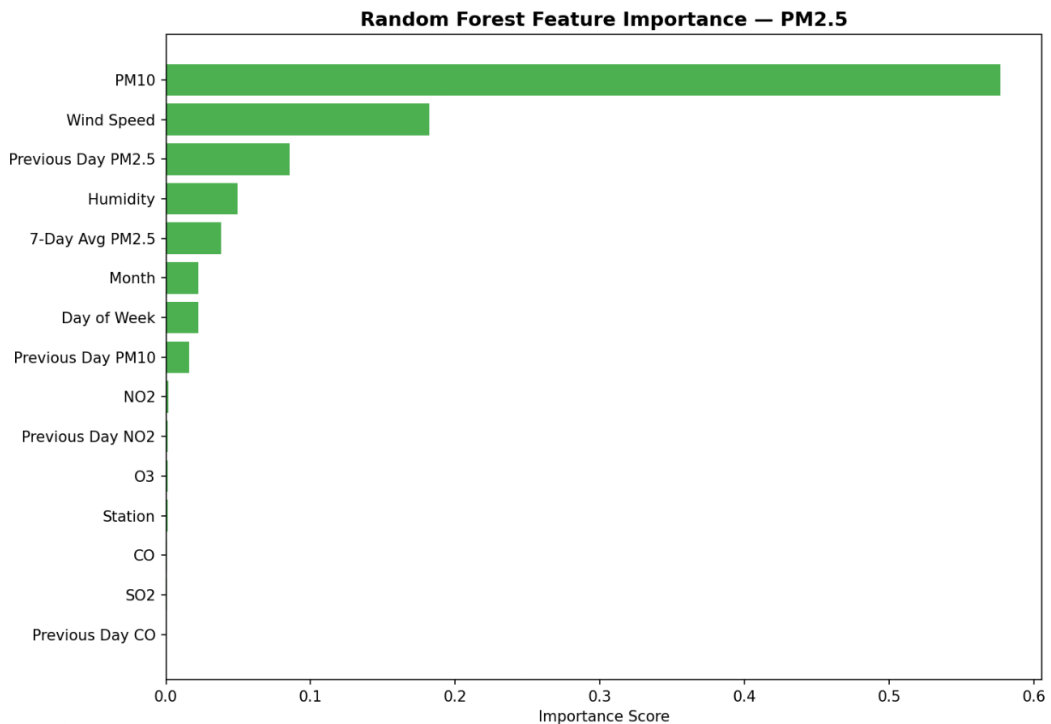


Fig. 3: Random forest feature importance PM2.5

(Source:) Created by the authors

Critical Insights regarding physical drivers of urban air quality were revealed with the analysis of Random Forest feature importance. As shown in the figure above, the strongest predictor for PM2.5 was the corresponding concentration of PM10 (importance score of ~0.57). Wind speed emerged as the second most important feature (~0.19). And the third most important was the previous day’s PM2.5 (~0.09).

Notably, the importance scores of pollutants (CO, NO₂, SO₂) were almost zero. An almost identical pattern emerged for PM10 targets, with PM2.5 as the most important predictor (~0.57) and wind speed ranking second again.

4.3 Correlation Analysis

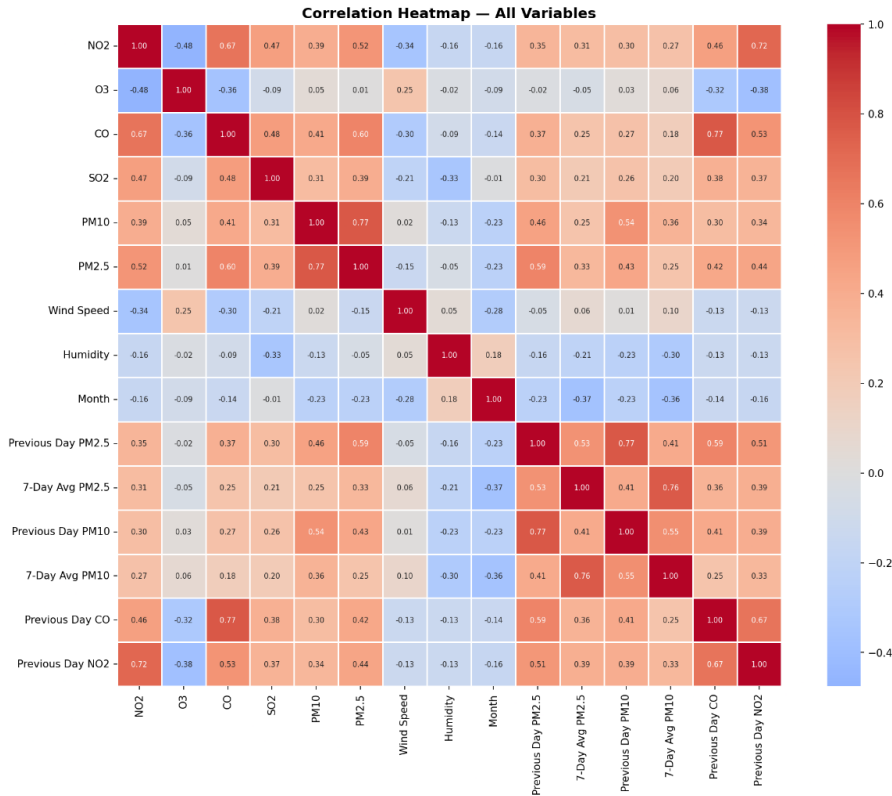


Fig. 4: Correlation heatmap
(Source:) Created by the authors

This figure shows the correlation analysis of any two given features. PM2.5 and PM10 showed a strong correlation of 0.77, suggesting common emission origins. CO showed a strong correlation with NO2 (0.67), while with PM2.5 it was 0.60.

4.4 Seasonal Patterns

The dataset showed profound seasonal volatility, aligning with regional meteorology. PM10 levels spiked sharply during spring, averaging 50.6 µg/m³ in March and 51.9 µg/m³ in April. This is a direct result of transboundary Asian dust storms, or Yellow Dust, originating from the Gobi Desert. Whereas, PM2.5 peaked during the winter (21-24 µg/m³). Both the pollutants reached their lowest point between July and September (with PM2.5 dropping to 9.3 µg/m³ in September), which was influenced heavily by the East Asian monsoon rains.

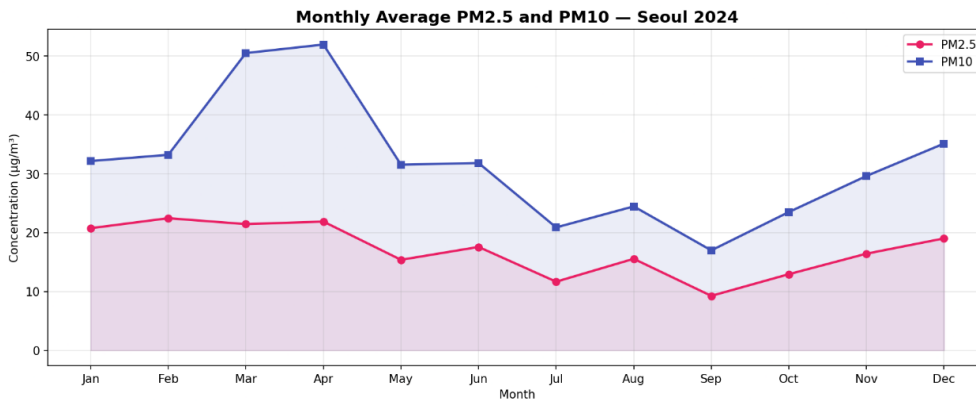


Fig. 5: Seasonal Trend

(Source:) Created by the authors

5.0 Discussion

The performance of Random Forest over the statistical baseline model provides confirmation that urban pollution is nonlinear and requires an ensemble model to be captured properly. The 17.5% improvement in R2 for PM2.5 shows that tree-based models can decipher complex interactions between atmospheric chemistry and meteorological states that linear geometries ignore.

The results challenge a common assumption in air quality modeling, that inclusion of pollutants such as SO₂ or NO₂ inherently improves PM prediction. Even though these gases are crucial factors of combustion-related exhaustion, the importance of direct fluctuation they provided was mild in a specific range of concerns within the framework of the model. But the data reveal that PM prediction is more dominated by the presence of other particulates, wind speed, and the previous day's PM levels. Yesterday's pollution is a vital baseline for today's forecast. In addition, vehicular traffic and industrial activity play crucial roles in emphasizing the need to pursue particulate forecasting more efficiently through direct pollutant interactions rather than trivial gaseous substances.

Importantly, seasonal patterns identified by the model mirror the previously documented climatological behavior of the Seoul metropolitan area (Lee et al., 2013). This validates both the integrity of the dataset collected and the model's learned representations. However, the most significant use of this study is its computational efficiency. The idea that an R2 of 0.832 and the training time of less than one second can be achieved on consumer-grade hardware challenges the assumption that effective machine learning requires expensive cloud infrastructure.

Since it can run locally, it can be configured to translate predictions into health advisories. It can be deployed in many developing cities across Asia and Africa, where the air quality monitoring network is expanding but sophisticated server tech is still under development.

From a practical point of view, integration into the world-wide health system is easily achieved with fairly low technical infrastructure needs and low investment. By translating predicted polluted substances into standard categories, local authorities can build an automated system that recommends to civilians about the upcoming air quality situation on time, such as limiting outdoor interaction or encouraging people to go outside with a facemask. This is specifically implementable for highly urbanized areas where pollution levels are increasing, whilst predictive infrastructures are not financially and technically focused.

6.0 Conclusion & Recommendations

This study successfully deployed and validated a lightweight machine learning framework for short-term prediction of PM_{2.5} and PM₁₀, using a 2024 dataset with data from 50 stations across Seoul. The proposed RF model significantly outperformed the statistical model, achieving an R2 of 0.832 (versus 0.708) for PM_{2.5} and 0.827 (versus 0.810) for PM₁₀. The study confirms that ensemble machine learning methods are superior when working with nonlinear patterns inherent in urban environments. This study proves that high-accuracy predictions don't always mean high-cost computing. The framework can be deployed in under a second and run predictions under half a second, which can be highly deployable for urban public health management.

Based on the findings, it would be useful if the local governments integrate lightweight machine learning frameworks into the existing physical monitoring to go from a passive observation system to active short-term forecasting. Furthermore, rapidly urbanizing cities across Asia and Africa should explore similar low-resource frameworks utilizing their respective open data portals for establishing independent forecast capabilities.

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Paper Contribution to the Related Field of Study

This research contributes to the field of urban environmental informatics and public health by demonstrating that a highly precise forecasting system can achieve impressive prediction accuracy (R2 = 0.832) while operating on low-resource, consumer-grade hardware. With training times under one second, it prioritizes efficient computation, and this research bridges the gap between complicated atmospheric modeling and local-level deployment in infrastructure-limited regions. Our findings show that PM prediction is

more dependent on temporal lag and meteorological variables rather than gaseous co-pollutants. In recent years, transformative technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and cloud computing have seen increasing demand across diverse sectors (Zhang et al., 2023). This insight provides a roadmap for IOT developers and urban planners to optimize sensor arrays on high-impact variables. Ultimately, this study enables local governments to implement reliable short-term air quality predictions for well-timed advisories.

Furthermore, the success of this study supports the viability of ensemble learning techniques for handling the nonlinear complexities of urban air sheds. By using Random Forest architectures, we quantified feature importance and confirmed that wind speed and previous pollutant concentrations are more critical than secondary gaseous factors for short-term accuracy. This shift away from resource-intensive deep learning toward highly interpretable, shallow models enables edge computing integration, where data is processed locally on the sensor node. Such an approach significantly reduces data transmission latency and bandwidth costs, making it an ideal framework for smart city initiatives in developing regions. As the global market for environmental monitoring systems continues to expand, the methodological efficiency demonstrated here provides a scalable blueprint for integrating real-time atmospheric intelligence into existing public health infrastructure without requiring expensive hardware overhauls.

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