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Short-Term Monitoring and Machine Learning-Based Forecasting of $PM_{2.5}$ in Dhulikhel Using a Calibrated Mid-Cost Sensor and Meteorological Parameters

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Abstract

This study presents a short-term monitoring and forecasting approach for fine particulate matter ($PM_{2.5}$) concentrations in Dhulikhel Municipality, Kavrepalanchok, Nepal, using calibrated mid-cost sensor and meteorological parameters. A 10-day co-location calibration of the mid-tier sensor (Aeroqual AQM 65) against the reference-grade GRIMM EDM 180 monitor yielded a strong linear correlation ($R^2 = 0.887$), and a resulting correction equation was applied to all subsequent data. Meteorological data and hourly $PM_{2.5}$ were collected over 42 days (April 22 to June 2, 2025). Mean $PM_{2.5}$ over study period was 22.62 µg/m³, with 90% of the monitoring days exceeded the safe limit of World Health Organization (WHO) 24-hour $PM_{2.5}$ guideline values of 15 µg/m³. Pollution rose analysis through software 'R' identified dominant pollutant transport from east-southeast and west-northwest directions, indicating contributions from road traffic corridors and regional transport from nearby cities. Four machine learning models: Random Forest, Extra Trees, eXtreme Gradient Boosting (XGBoost), and a Stacking ensemble were trained and evaluated for 1–6 hour ahead forecasting. The Stacking model demonstrated the most consistent performance across all forecast horizons, achieving the highest performance ($R^2 = 0.844$, RMSE = 3.29 µg/m³ for current hour estimation using combined inputs). Inclusion of meteorological parameters significantly enhanced model accuracy. These findings confirm the feasibility of combining calibrated mid-cost sensors with ensemble machine learning for reliable short-term air quality forecasting in resource-scare region, supporting evidence-based pollution management and public health interventions.

Keywords: *Co-location calibration, machine learning, meteorological parameters, mid-cost sensors, $PM_{2.5}$, short-term forecasting*

1. Introduction

Particles of fine particulate matter ($PM_{2.5}$) that have an aerodynamic diameter of less than 2.5 µm are known to be extremely dangerous to both human health and the environment. Because of their tiny size, $PM_{2.5}$ particles enter the respiratory system deeply, build up in the alveoli, and cause asthma, bronchitis, cardiovascular disease, and early death. (Gurung & Bell, 2012; WHO, 2021). In Nepal, the burden of $PM_{2.5}$ pollution is particularly acute in rapidly urbanizing regions where industrial growth, vehicular traffic, and household combustion converge.

Nepal faces mounting air quality challenges, with research largely concentrated in the Kathmandu Valley and major cities. (Neupane et al., 2022). Semi urban areas like Dhulikhel, which is about 30 km east of Kathmandu along the Araniko Highway at an elevation of roughly 1,550 m above sea level, are still largely unmonitored in spite of growing urbanization, regional pollution transport, increasing vehicle emissions, and increased building construction activity. (Gurung & Bell, 2012). This monitoring gap limits understanding of local pollution dynamics and constrains targeted public health responses.

Although accurate, traditional reference-grade air quality monitors are too costly and logistically complex for small towns. When carefully calibrated against reference-grade monitors like the GRIMM

EDM 180 using co-location techniques, mid-cost instruments like the Aeroqual AQM 65 provide a cost-effective and workable substitute. (Bioto et al., 2023; Thapa & Devkota, 2024).

In addition to monitoring, proactive air quality management and public health alert systems depend on Particulate pollution concentration predictions. When it comes to simulating the intricate, non-linear correlations between meteorological conditions and $PM_{2.5}$ concentrations, machine learning (ML) methods such as Random Forest (RF), Extra Trees, eXtreme Gradient Boosting (XGBoost), and ensemble Stacking have demonstrated improved performance compared with conventional statistical forecasting approaches. (Alrashidi et al., 2025). Meteorological parameters such as temperature, relative humidity, wind speed, and solar radiation consistently improve forecasting accuracy when incorporated into different machine learning models (Ma et al., 2023; Wang & Ogawa, 2015).

To validate and calibrate the Aeroqual AQM 65 mid-cost sensor by co-locating it with the GRIMM EDM 180 reference monitor; evaluate short-term temporal trends, diurnal patterns, and dominant source directions of $PM_{2.5}$ in Dhulikhel; and to compare how well four machine learning models forecast $PM_{2.5}$ for lead times of one to six hours, both with and without meteorological inputs are the three major objective of this study. This study fills a significant methodological and data gap in Nepal's semi-urban air quality management.

2. Materials and Methods

Workflow followed in this study is represented in Figure 1. The process began with data collection and preprocessing, followed by analytical and modeling procedures. Subsequently, model performance was then evaluated using validation metrics, and the final results were interpreted to achieve the study objectives.

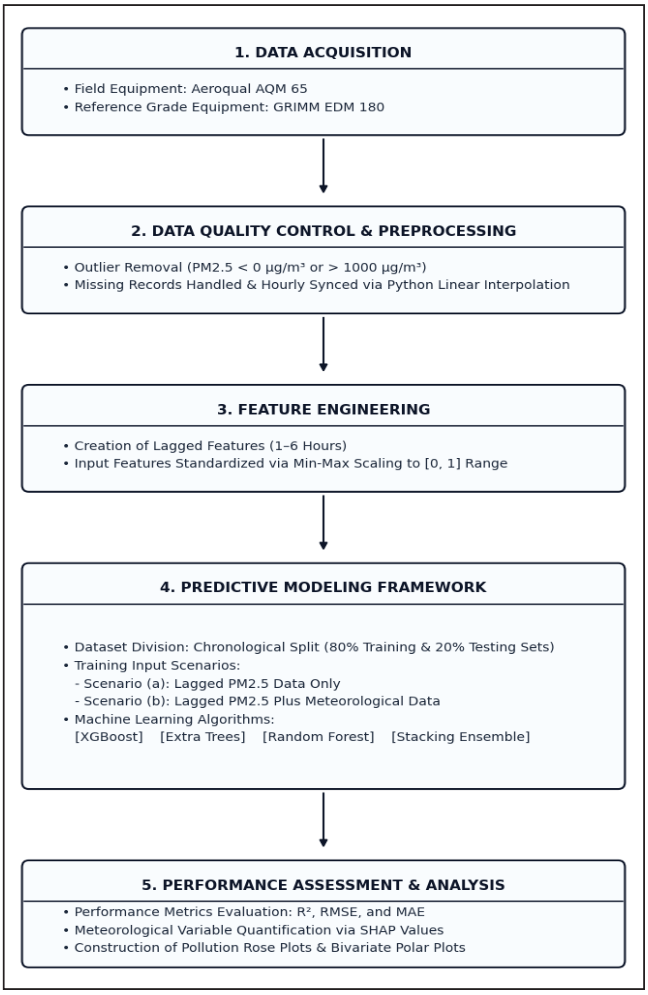

Figure 1: Flowchart illustrating the overall methodological framework adopted in this study

2.1 Study Area

The study was carried out at an elevation of roughly 1,550 meters above sea level on the rooftop of Kathmandu University located in Dhulikhel Municipality, Kavrepalanchok District, Bagmati Province, Nepal (27°37'8.40"N, 85°32'19.29"E), which is located approximately 35 kilometers North-east of Kathmandu. The Study area is situated near the Araniko Highway, a vital transportation route that connects Kathmandu to both the Chinese border and eastern Nepal. The monitoring station was positioned about an aerial distance of 500m from the Araniko highway, 30 m above the ground deployed on the rooftop of a 3 story university building, with the sampling inlets positioned 1.5 m above the rooftop surface level. Dhulikhel is a strategically significant location for $PM_{2.5}$ monitoring and forecasting because of the pollutant

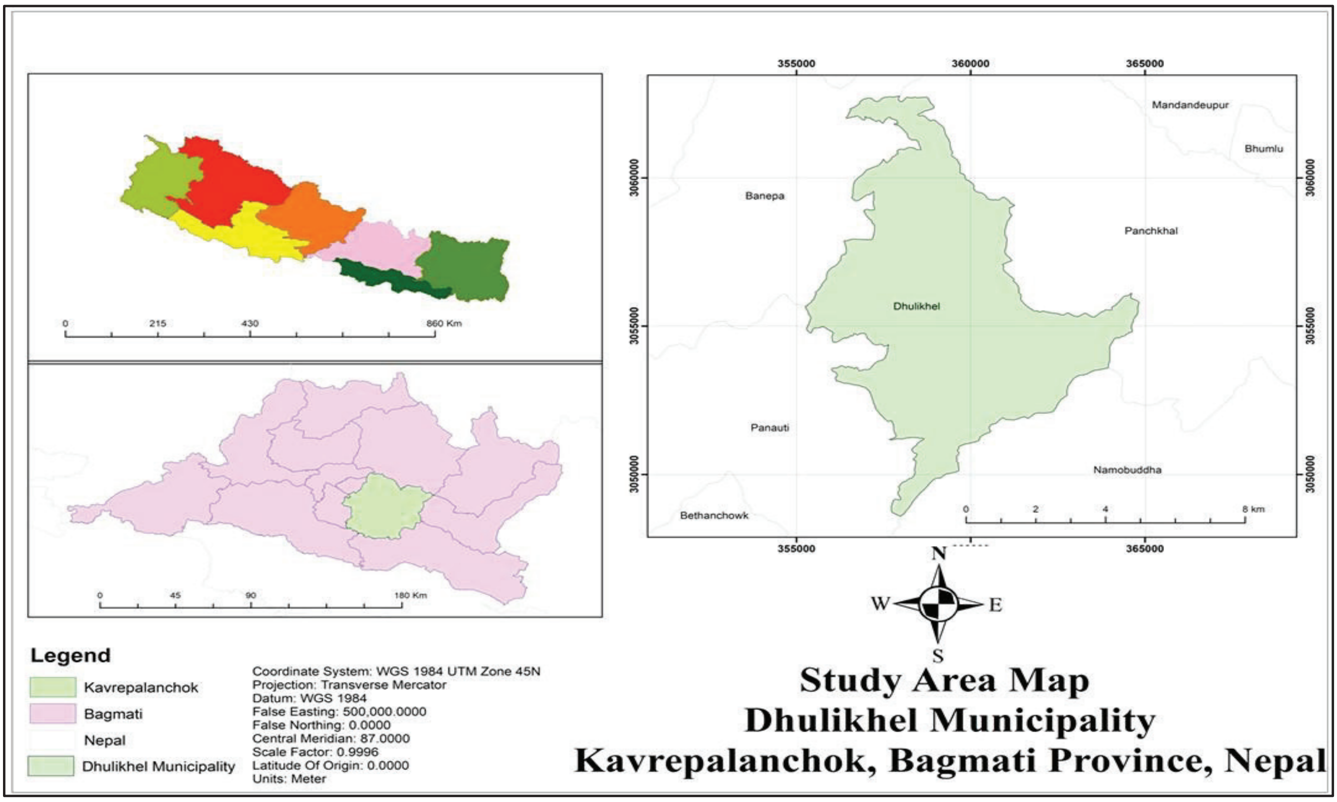

Figure 2: Study area map showing the location of Dhulikhel Municipality, Kavrepalanchok, Bagmati Province, Nepal

transport from the capital, topography and increased local air pollution pressures.

2.2 Instrumentation

In this study two instruments were employed, Aeroqual AQM 65, a modular ambient air monitoring station from which up to 20 contaminants and environmental factors can be measured in real time. For particulate matter monitoring, the AQM 65 utilizes an integrated optical particle counter (OPC) module that uses right-angle light scattering via a laser diode to count and size individual suspended particles (Aeroqual, 2025). The reference-grade instrument was the GRIMM EDM 180, a Federal Equivalent Method (FEM) for $PM_{2.5}$ that was approved under UK-MCERTS and CN-CMA standards and authorized by the US EPA. With an integrated Nafion dryer and purge air system, it uses optical light scattering over 31 particle size channels to quantify particulate concentrations (DURAG Group, 2019). To ensure identical ambient air sampling and minimize spatial micro-variation, both instruments were positioned with their sampling inlets at a matching height of 1.5 meters above ground level and spaced within 1 meter of each other.

2.3 Co-location Calibration

Between April 12 and April 21, 2025, a 10-day co-location calibration was carried out at the ICIMOD facility (Khumaltar air quality monitoring station) in Khumaltar, Lalitpur where both sensors were placed side by side in ambient circumstances. For low or mid-tier sensor measurements against reference-grade, co-location calibration is a commonly used approach to assess sensor performance and develop correction factors (Wang & Ogawa, 2015). A correction equation was obtained by comparing simultaneous hourly $PM_{2.5}$ data using linear regression analysis:

$$\textit{Corrected } PM_{2.5} = 1.213 \times \textit{Raw Aeroqual } PM_{2.5} + 3.594$$

The calibration yielded $R^2 = 0.887$, RMSE = 5.481 µg/m³, MAE = 4.353 µg/m³, and MBE = 0.000 µg/m³, confirming strong agreement and near-zero systematic bias. All corrected $PM_{2.5}$ values were applied to subsequent monitoring data with the help of corrected equation.

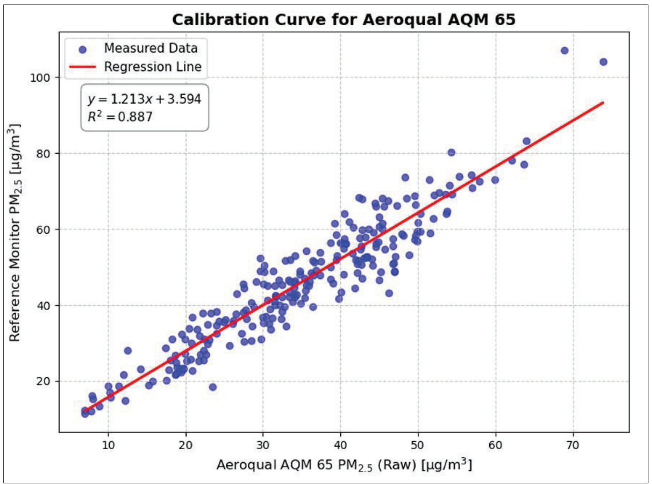

Figure 3: Calibration curve and scatter plot showing Aeroqual AQM 65 vs. GRIMM EDM 180 reference $PM_{2.5}$ measurements ($R^2 = 0.887$)

2.4 Data Collection

After calibration, the Aeroqual AQM 65 was set up on the study area i.e roof of the library at Kathmandu University in Dhulikhel, where it continuously recorded hourly $PM_{2.5}$ concentrations for 42 days, from April 22 to June 2, 2025. The Department of Hydrology and Meteorology (DHM) provided the required concurrent hourly meteorological data frommonitoring station in Dhulikhel which is about 1 km in aerial distance, including temperature (°C), relative humidity (%), wind speed (m/s), and wind direction (°). Data on solar radiation and dew point temperature were obtained for the same time period from the closest DHM station in Panauti.

2.5 Data Preprocessing

According to normal air quality processing standards, $PM_{2.5}$ values below 0 µg/m³ or above 1000 µg/m³ were removed as outliers as a fundamental part of data quality control. Unrealistic or missing numbers in meteorological records were not included. Linear interpolation through Python was used to fill the remaining short term gaps in the datasets. The meteorological and $PM_{2.5}$ datasets were then synced hourly. For predictive modeling, lagged features (1–6 hours) of $PM_{2.5}$ and meteorological factors were created. The lagged features were introduced to capture the temporal dependencies and delayed atmospheric effects on $PM_{2.5}$ over time. To maintain the sequential nature of the time series data, the dataset was chronologically divided into 80% training and 20% testing sets after all input features were standardized using Min-Max scaling to the [0, 1] range.

2.6 Machine Learning Models

Four machine learning algorithms were used for the predictive modeling for current and future hours: (i) XGBoost, a scalable gradient boosting framework with regularization and parallel processing (Chen & Guestrin, 2016); (ii) Extra Trees, a variant of Random Forest with extra randomness through random split selection (Geurts et al., 2006); (iii) a Stacking ensemble that combines predictions from Random Forest, Extra Trees, and XGBoost through a meta-learner (Tian et al., 2024). To evaluate the predictive impact of weather factors, two explicit input scenarios were designed to forecast $PM_{2.5}$ at time t and future steps (e.g., *t+1 to t+6*).

- **Scenario A :** (Lagged $PM_{2.5}$ only **):** Consisted of 6 features representing historical $PM_{2.5}$ concentrations from (*t-1*) to (*t-6*) hours.
- **Scenario B** : (Lagged $PM_{2.5}$ + Meteorology): Combined the 6 lagged $PM_{2.5}$ features with 6 hourly lags (*t-1 to t-6*) of all meteorological variables

R^2, RMSE, and MAE were used to assess performance of each model. Pollution rose plots and a bivariate polar plot were constructed using R (v4.3.0) with the openair package. SHAP values were calculated to quantify the relative contribution of each meteorological variable to model predictions.

3. Results and Discussion

3.1 Sensor Calibration Performance

Table 1: Performance metrics of the corrected Aeroqual AQM 65 $PM_{2.5}$ data against the GRIMM EDM 180 reference monitor

Metric	Value
R^2 (Coefficient of Determination)	0.887
MAE (Mean Absolute Error)	4.353 µg/m³
RMSE (Root Mean Squared Error)	5.481 µg/m³
MBE (Mean Bias Error)	0.000 µg/m³

When calibrated under local ambient circumstances with reference grade sensor, the Aeroqual AQM 65 consistently captured $PM_{2.5}$ temporal patterns and magnitudes, as demonstrated by the co-location calibration's strong linear relationship ($R^2 = 0.887$) (Table 1), indicating that the calibrated sensor is suitable for indicative monitoring applications in semi-urban environments. While the RMSE and MAE values of 5.481 and 4.353 µg/m³, respectively, are within acceptable bounds for ambient air quality monitoring, the MBE of 0.000 µg/m³ suggests almost zero systematic bias. These findings are in line with those of Bioto et al. (2023) who found similar agreement between regulatory-grade monitors and Aeroqual sensors when co-location guidelines were followed.

Shapiro-Wilk residual normality tests showed that AQM 65 performed reliably in the moderate (30–60 µg/m³, $p = 0.861$) and high (>60 µg/m³, $p = 0.300$) $PM_{2.5}$ ranges. A significant deviation from normality was observed in the low (<30 µg/m³) range ($W = 0.937$, $p = 0.021$), consistent with the known limitations of optical mid-cost sensors at low particulate concentrations, where signal-to-noise ratios are reduced (Barkjohn et al., 2022).

3.2 $PM_{2.5}$ Concentration Trends

The $PM_{2.5}$ concentration trends has been discussed in table 2 and graphically presented in figure 4.

Table 2: Summary statistics of daily $PM_{2.5}$ concentrations recorded in Dhulikhel (April 22 – June 2, 2025)

Statistic	Value (µg/m³)
Minimum	9.80
Maximum	37.26
Mean	22.62
Standard Deviation	6.84
WHO (15 µg/m³) Exceedance Days	38 out of 42
NAAQS (40 µg/m³) Exceedance Days	0 out of 42

Over the time of the 42-day monitoring period, daily $PM_{2.5}$ ranged from 9.80 to 37.26 µg/m³, with a mean of 22.62 µg/m³ (Table 2). The observed mean concentration (22.62 µg/m³ was 1.5 times higher than the WHO guideline value, indicating a persistent public health concern despite compliance with Nepal's national standard. The WHO 24-hour $PM_{2.5}$ safe limit of 15 µg/m³ was surpassed on 38 days (90%). No day exceeded Nepal's NAAQS threshold of 40 µg/m³, demonstrating both national regulatory compliance and a clear discrepancy between national norms and global health-based targets. This discrepancy highlights the need for stricter national standards to sufficiently protect public health and is consistent with findings from studies conducted in the Kathmandu Valley (Neupane et al., 2022).

Bimodal diurnal trend was observed through the hourly $PM_{2.5}$ concentrations. Early in the morning (6:00–9:00 AM) and late at night (6:00–9:00 PM) saw the highest levels of $PM_{2.5}$ concentrations. Concentrations were consistently lower in the afternoon (12:00–4:00 PM), most likely due to increased boundary layer mixing and wind-driven dilution. This pattern reflects common regional emission cycles associated with household

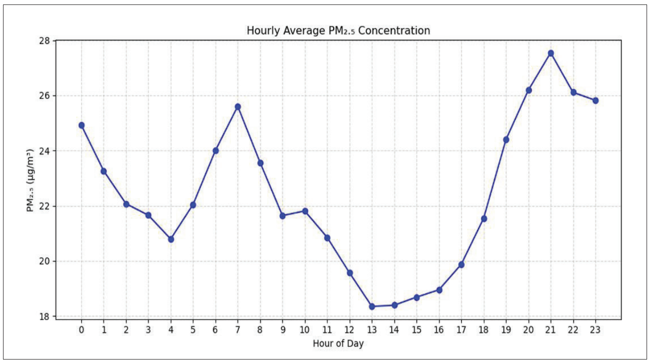

Figure 5: Mean hourly $PM_{2.5}$ concentration over the study period showing bimodal diurnal pattern with morning (6:00–9:00 AM) and evening (6:00–9:00 PM) peaks

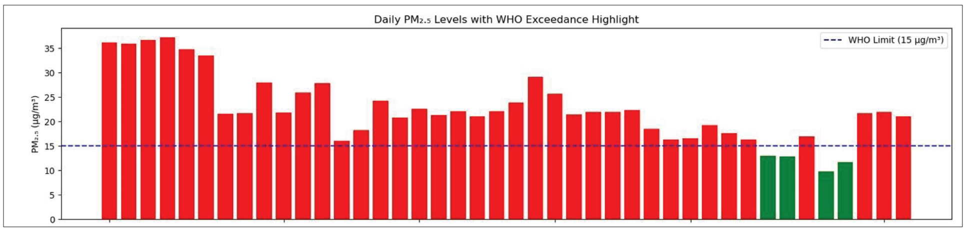

Figure 4: Daily average $PM_{2.5}$ concentration over the study period (April 22 – June 2, 2025) with the WHO 24-hour guideline (15 µg/m³).

combustion and road traffic activity, and it is consistent with observations from the Kathmandu Valley (Gurung & Bell, 2012).

3.3 Pollution Rose and Source Direction Analysis

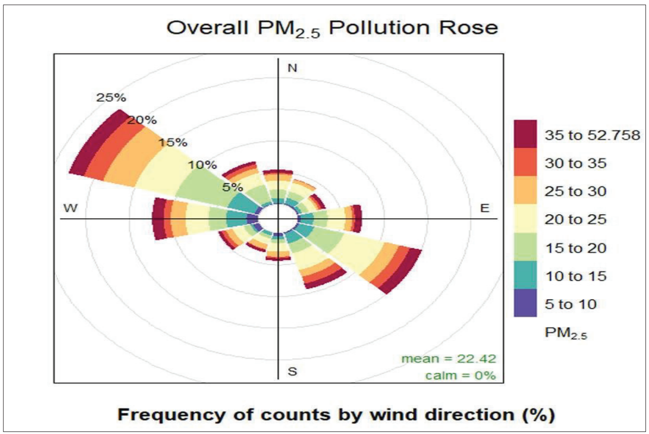

Figure 6: Overall pollution rose for $PM_{2.5}$ during the study period indicating dominant source directions (WNW and ESE) associated with elevated concentrations

According to pollution rose analysis $PM_{2.5}$ concentrations were consistently linked to the West-northwest (WNW) and east-southeast (ESE) winds. With values often surpassing 35 µg/m³, the WNW sector had the highest frequency (up to 25%). Elevated levels were also observed in the ESE region, indicating possible contributions from pollution transport from the Araniko Highway and nearby cities. These directional patterns are consistent with pollution rose analyses from Bangkok (Anusasananan et al., 2023) where large traffic regions, nearby cities and industrial source zones were correlated with dominant wind directions.

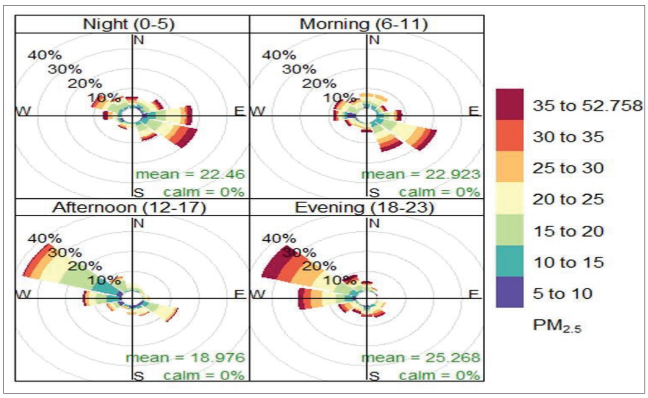

Figure 7: Pollution rose for $PM_{2.5}$ during the different time of the day during study period.

A time-of-day analysis revealed that the afternoon (12:00–17:00) had the lowest mean $PM_{2.5}$ (18.98 µg/m³) and the evening (18:00–23:00) had the highest (25.27 µg/m³). Despite identical wind patterns, night time concentrations (mean: 23.86 µg/m³) were higher than daytime levels (mean: 20.96 µg/m³). This was caused by persistent boundary layers, less atmospheric mixing, and the buildup of emissions from burning biomass under poor ventilation. With averages of 22.14 and 23.09 µg/m³, respectively, weekday and weekend pollution rose demonstrated similar directional tendencies and persistently exceeded the WHO standard.

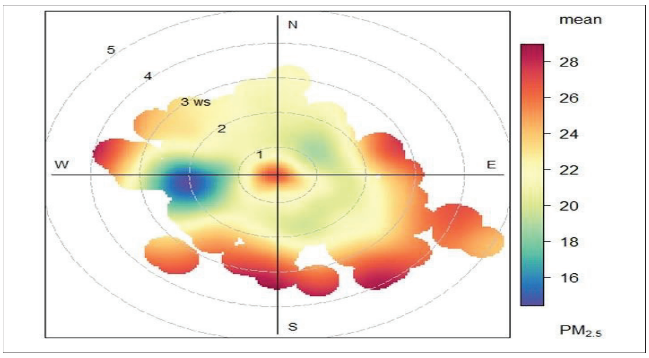

Figure 8: Bivariate polar plot of $PM_{2.5}$ concentration with wind speed and direction showing elevated concentrations (e"26 µg/m³) associated with moderate winds (1.5–3.5 m/s) from the east, southeast, and southwest

Through the bivariate polar plot analysis, it further revealed that elevated $PM_{2.5}$ (≥26 µg/m³) was predominantly associated with moderate wind speeds (1.5–3.5 m/s) from the east, southeast, and southwest, suggesting regional pollutant transport from urban sources such as Banepa, and Kathmandu Valley and major highway corridors. Wind speeds exceeding 4 m/s were consistently linked to lower $PM_{2.5}$, confirming the role of atmospheric mixing in pollutant dilution.

3.4 Machine Learning Model Performance

3.4.1 Forecasting using historical $PM_{2.5}$ Data Only

When trained on lagged $PM_{2.5}$ datasets alone Extra Trees had the highest current-hour performance (R^2 = 0.789, RMSE = 3.82 µg/m³, MAE = 2.73 µg/m³), which was closely followed by Random Forest and Stacking model (both R^2 = 0.787) while the performance of XGBoost was comparatively

Table 3: Performance of machine learning models for current-hour $PM_{2.5}$ estimation using lagged historical $PM_{2.5}$ data only

Model	R^2	RMSE (µg/m³)	MAE (µg/m³)
Random Forest	0.787	3.84	2.69
XGBoost	0.733	4.30	3.01
Extra Trees	0.789	3.82	2.73
Stacking	0.787	3.84	2.73

low (R^2 = 0.733). Stacking model was the most consistent for forecasting one to six hours in advance, retaining R^2 = 0.737 at one hour and dropping to 0.527 at six. With R^2 = 0.374 at 6 hours and RMSE = 6.60 µg/m³, XGBoost experienced the steep decline, making it unsuitable for longer forecast horizons with PM data alone. Short-term air quality forecasting is known to be limited by this steady performance decrease with increasing lead time (Alrashidi et al., 2025).

3.4.2 Forecasting Using Historical $PM_{2.5}$ and Meteorological Data

Table 4: Performance metrics of machine learning models for current-hour $PM_{2.5}$ estimation using combined historical $PM_{2.5}$ and meteorological data

Model	R^2	RMSE (µg/m³)	MAE (µg/m³)
Random Forest	0.824	3.49	2.45
XGBoost	0.829	3.43	2.45
Extra Trees	0.847	3.25	2.28
Stacking	0.844	3.29	2.30

After the addition of lagged meteorological variables model performance was significantly enhanced. Extra Trees obtained the best current-hour accuracy (R^2 = 0.847, RMSE = 3.25 µg/m³, MAE = 2.28 µg/m³), followed by Stacking (R^2 = 0.844, RMSE = 3.29 µg/m³). In line with Wang and Ogawa (2015) and Ma et al., (2023), these improvements over using PM-only models for forecasting validate the

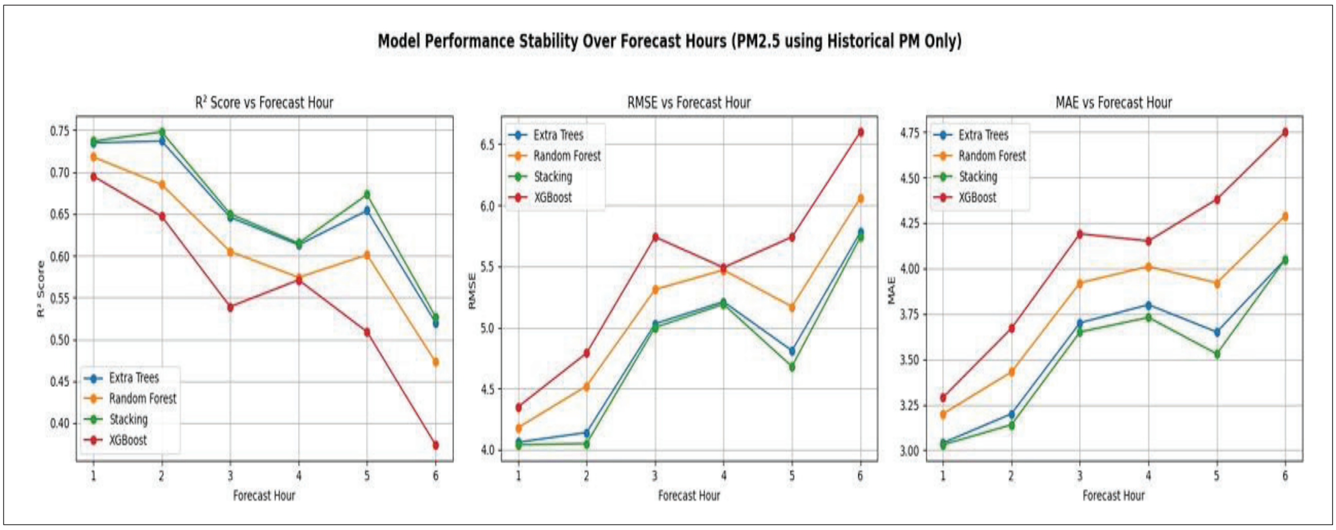

Figure 9: Comparison of model stability for 1–6 hour $PM_{2.5}$ prediction using combined meteorological and $PM_{2.5}$ data showing R^2, RMSE, and MAE trends across forecast horizons

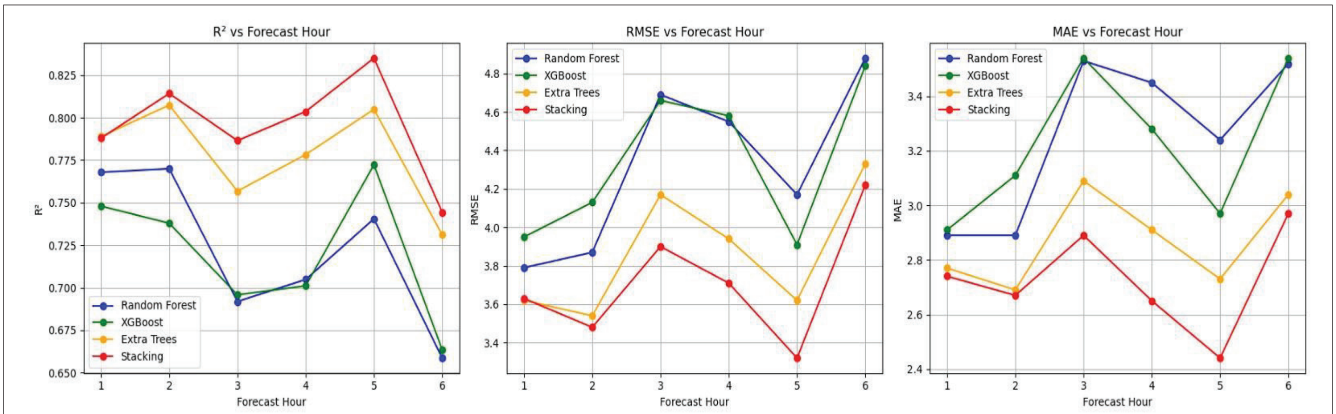

Figure 10: Comparison of model stability for 1–6 hour $PM_{2.5}$ prediction using combined meteorological and $PM_{2.5}$ data showing R^2, RMSE, and MAE trends across forecast horizons

significance of meteorological factors in modifying $PM_{2.5}$ dynamics.

Out of all models, Stacking model consistently performed better than the others for multi-hour forecasting with combined inputs, obtaining R^2 values above 0.74 over all 1–6 hour horizons. The model's ability to use meteorological dynamics for medium-term forecasts was demonstrated by performance at the 5-hour horizon (R^2 = 0.835, RMSE = 3.32 µg/m³), which outperformed several shorter horizons. According to Tian et al., (2024) and To Thi Hien et al. (2021), because of its ability to combine complementary base learner capabilities through a meta-learner stacking is preferable. For predictions lasting one to two hours, Extra Trees performed similarly, but after three hours, accuracy loss was observed in XGBoost and Random Forest.

3.4.3 SHAP Feature Importance of Meteorological Variables

By SHAP analysis Dew point temperature was shown to be the most dominant meteorological driver of $PM_{2.5}$ (mean SHAP value: 3.59 µg/m³), which influences aerosol hygroscopic growth and secondary particulated formation, indicating its considerable correlation with pollutant condensation processes and atmospheric moisture content. This indicates that ambient moistures strongly governs secondary aerosol formation, where higher moisture accelerates the hygroscopic growth of particles. This thermodynamic dominance aligns with findings by Li et al. (2017) in Hong Kong. Relative humidity (1.19 µg/m³) was next most significant predictors and ambient temperature (1.06 µg/m³), which influenced particle production and dispersion through chemical and physical interactions. The mild impact of solar radiation (0.99 µg/m³) may be related to photochemical processes. Conversely, dynamic variables such as contributions from wind direction and wind speed yielded minor contributions. While higher wind speeds typically promote mechanical dispersion as observed in high ventilation regions like Hanoi, the minimal impact here implies that local conditions were likely characterized by stagnant air masses where localized chemical accumulation overrode regional transport. In general, thermodynamic variables had a stronger impact than dynamic variables, which is in line with research from Hong Kong (Li et al., 2017) and Hanoi (Hien et al., 2002).

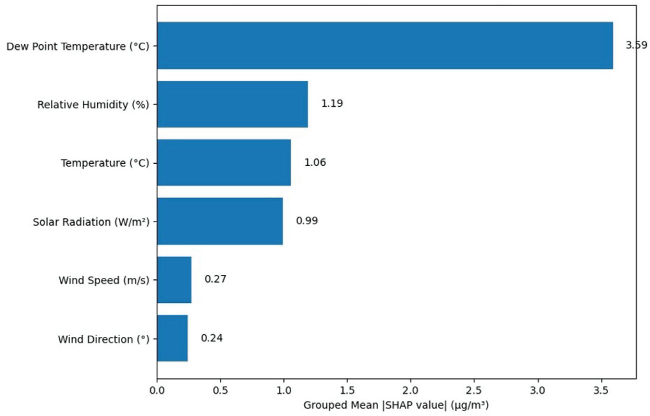

Figure 11: Grouped SHAP feature importance of meteorological variables showing relative contribution (mean |SHAP value| in µg/m³) to $PM_{2.5}$ model predictions

4. Conclusion

For short-term $PM_{2.5}$ monitoring and forecasting in semi-urban and resource scare region, this study shows the feasibility of using a calibrated mid-cost sensor in conjunction with meteorological parameters for machine learning-based predictions. The Aeroqual AQM 65's co-location calibration against the reference grade sensor (GRIMM EDM 180) produced a reliable correction model (R^2 = 0.887) with almost no systematic bias, confirming the sensor's usability for ambient monitoring in the resource scare regions. While staying under Nepal's NAAQS (40 µg/m³), $PM_{2.5}$ concentrations in Dhulikhel continuously exceeded the WHO 24-hour limit safe limit of (15 µg/m³) on 90% of monitoring days during the pre-monsoon period. Vehicle activity on the nearby Highways and regional transport from nearby cities are identified as the possible main sources of particulate pollution due to the unique bimodal diurnal pattern and the predominant pollution transfer from WNW and ESE directions.

In case of machine learning based predictions, for all 1–6 hour forecast horizons, the Stacking ensemble model performed better and more consistently (R^2 = 0.844 for current-hour estimation with mixed inputs). After the integration of meteorological factors Forecast accuracy of all models was much improved. A scalable and economic framework for managing air quality in secondary urban areas with limited resource for air quality management is provided by this integrated strategy combining calibrated mid-cost monitoring with ensemble machine learning.

Future research should focus on extending the monitoring period to capture seasonal variability, conduct source appointment of the particulate pollution, deploy multiple sensors and study spatial variation of the pollutants to characterize heterogeneity, and investigate deep learning approaches for longer forecast horizons. Integration of real-time $PM_{2.5}$ forecasts into public health alert systems is also recommended to protect vulnerable populations during high pollution episodes.

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