Explainable Machine Learning for Air Pollution Level Prediction and Contributing Factor Analysis

Shiva Kumar[1], Dr. M K Jayanthi Kannan[2]
[1] PG Student, School of Computing Science, Engineering and Artificial Intelligence (SCAI), VIT Bhopal University, Bhopal-Indore Highway, Kothrikalan, Sehore, Madhya Pradesh - 466114.
[2]Professor, School of Computing Science, Engineering and Artificial Intelligence (SCAI), VIT Bhopal University, Bhopal-Indore Highway, Kothrikalan, Sehore, Madhya Pradesh - 466114.

***Abstract*—Air pollution is a major environmental concern, and short-term forecasting of fine particulate matter (PM2.5) supports monitoring, public awareness, and informed decision-making. The "AirInsight" platform is designed as an explainable PM2.5 prediction system that applies machine-learning regression to historical air-quality observations from the Anand Vihar (Delhi, DPCC) monitoring site and forecasts the PM2.5 concentration one hour ahead. With features including data cleaning and timestamp auditing, a leakage-free one-hour-ahead target, chronological model evaluation, feature-contribution explanations, and an interactive dashboard, AirInsight aims to make air-quality forecasts transparent and reproducible. Linear Regression and Random Forest are compared against a persistence baseline using MAE, RMSE, and R^2. On the chronological test set (2,797 rows), Linear Regression achieved MAE 15.477, RMSE 21.539 and $R^2 = 0.7116$; Random Forest achieved MAE 15.734, RMSE 22.507, and $R^2 = 0.6851$, while the persistence baseline achieved MAE 14.583, RMSE 21.342, and $R^2 = 0.7169$. The persistence baseline therefore matched or beat both trained models, showing that strong autocorrelation limits the value of current-hour features and motivating lagged features. Feature contributions describe model behaviour and are not evidence of emission sources.**

***Index Terms*—PM2.5, Air-Quality Prediction, Machine Learning, Explainable AI, SHAP, Linear Regression, Random Forest, Persistence Baseline, Dashboard.**

I. INTRODUCTION

The increasing severity of urban air pollution, coupled with the growing interest in data-driven environmental monitoring, underscores the necessity of reliable predictive models for air quality. PM2.5 (particulate matter with an aerodynamic diameter of 2.5 μm or less) varies strongly with time of day, season, meteorology, and local emissions, making it challenging to anticipate from individual readings. The "AirInsight" platform is designed as an intelligent, explainable air-pollution prediction system that simplifies the interpretation of forecasts through data analytics and machine-learning techniques. AirInsight integrates modern technology with environmental analysis to enhance transparency of predictions. The platform offers features such as one-hour-ahead PM2.5 forecasting, model comparison, feature-contribution explanations, and a user-friendly dashboard, ensuring seamless interaction between users and model outputs. The scientific rationale lies in several key aspects. Firstly, regression models learn the relationship between current pollutant, weather, and time features and the next-hour PM2.5 value. Secondly, a chronological evaluation with a persistence baseline reveals whether a model shows real forecasting skill. Additionally, explainable AI methods such as SHAP [4] estimate how each feature contributes to a prediction, enhancing user trust. By combining prediction, evaluation, and explanation, AirInsight aims to support transparent air-quality forecasting. The review of NIST-recommended cryptographic schemes for the post-quantum era [21] addresses the need to prepare security infrastructures for potential quantum-computing threats. Integrating AI, secure computing, data analytics, and emerging technologies can support more reliable, privacy-aware, and intelligent digital systems. The user interface design with respect to users' viewing experience across static and dynamic websites. It highlights the importance of website presentation and content delivery in

supporting usability and improving the overall user experience [22]. The automatic content creation and rearrangement mechanism improves cloud storage space utilization. Organizing digital content efficiently, with potential benefits for storage management and resource optimization in cloud-based environments [13].

II. LITERATURE REVIEW OF EXISTING SYSTEMS

The reviewed research covers interpretable machine learning for air-pollution forecasting, AI-based air-quality monitoring and forecasting, and model-explanation frameworks. The methodology of these works includes: Data Collection from monitoring-station observations and meteorological records. Prediction Model Development using statistical, machine-learning, and deep-learning models. Explanation using feature-attribution methods. In terms of efficiency, the surveyed approaches improve forecasting accuracy, handle nonlinear relationships and, when explanation methods are added, make predictions easier to interpret. Cybersecurity, authentication, cloud computing, and machine learning: Research on cybersecurity has examined threats and countermeasures across networked systems, cloud platforms, and user authentication mechanisms. The work on protecting confidential data over distributed cloud storage [5] addresses the importance of safeguarding sensitive information in distributed environments, while the book on network security attacks and countermeasures [6] provides a broader foundation for understanding attack models and defensive strategies. Image-based authentication using randomized selection [7] and the performance analysis of bag-of-password authentication across Python, Java, and PHP implementations [8] explore approaches to improving authentication security and implementation efficiency. Research on cybercrime and open-source software [9], strategic information-security planning using decentralized identity mechanisms [10], and machine-learning techniques for malware detection [11] further highlight the need for layered security, proactive threat detection, and user-oriented protection. The hybrid deep-learning approach for intrusion detection in AWS cloud environments [12] extends this direction by applying intelligent methods to cloud security, while the survey of confidential-data protection in distributed storage [5] emphasizes data privacy and secure storage as essential concerns. Collectively, these studies establish a foundation for combining authentication, intrusion detection, machine learning, and secure cloud architecture to address increasingly complex cyber threats.

II.1 The research explores multiple objectives

Air-Quality Forecasting to estimate future pollutant concentrations. Model Evaluation to compare candidate algorithms. Interpretability to explain which inputs drive predictions. Challenge Analysis to identify data-quality and generalization issues. The study employs advanced technologies, including machine learning algorithms (regression, ensembles, deep learning) for trend prediction. Explainable AI (SHAP and related methods) for feature attribution. Statistical Software (Python) for data analysis. The methodology integrates: Quantitative Analysis of pollutant and weather time series. Comparative Analysis of different models. Systematic Review of published studies. Regarding efficiency, the studies ensure: Improved Prediction Accuracy through model selection. Interpretability through explanation methods. Scalability for different stations and pollutants. Despite their strengths, the studies highlight challenges such as: Data Quality Issues (missing values, sensor faults). Temporal Leakage if evaluation is not chronological. Limited Generalisation across stations and seasons. Explanation Misreading, where model contributions are mistaken for causes.

Table 1: Literature review of air-pollution prediction and explainability.

Paper	Objective used	Technology used	Methodology used	Efficiency	Issues
Title: Interpretable ML Approaches for Forecasting and Predicting Air Pollution: A Systematic Review. **Journal:** Aerosol and Air Quality Research. **Year:** 2024. **DOI:** 10.4209/aaqr.230151 [1]	1. Review interpretable ML for air-pollution forecasting. 2. Motivate explanation alongside accuracy.	1. Interpretable ML models. 2. Explainable AI methods.	1. Systematic literature review. 2. Comparison of approaches.	1. Consolidates interpretable approaches. 2. Supports accuracy plus interpretability.	1. Not dataset-specific validation. 2. Findings do not rank This project's models.
Title: Application of AI in Air Pollution Monitoring and Forecasting: A Systematic Review. **Journal:** Environmental Modelling & Software. **Year:** 2025. **DOI:** 10.1016/j.envsoft.2024.106312 [2]	1. Review AI for monitoring and forecasting. 2. Summarise modelling approaches.	1. AI/ML models. 2. Monitoring data sources.	1. Systematic review of methods and challenges.	1. Summarises the range of data and modelling approaches.	1. Broad review, not project evidence.
Title: A Systematic Scrutiny of AI-Based Air Pollution Prediction Techniques, Challenges, and Viable Solutions. **Journal:** Journal of Big Data. **Year:** 2024. **DOI:** 10.1186/s40537-024-01002-8 [3]	1. Examine AI prediction techniques. 2. Identify challenges and solutions.	1. AI-based prediction techniques.	1. Systematic review and critical scrutiny.	1. Highlights challenges and possible solutions.	1. Does not evaluate this project's dataset.
Title: A Unified Approach to Interpreting Model Predictions (SHAP). **Venue:** NeurIPS 30. **Year:** 2017 [4]	1. Explain individual model predictions consistently.	1. Shapley-value feature attribution.	1. Additive feature-attribution framework.	1. Consistent local and global explanations.	1. Explains the model, not real-world causes.

Interpretable Machine Learning for Air-Pollution Forecasting

"Interpretable Machine Learning Approaches for Forecasting and Predicting Air Pollution" [1] systematically reviews interpretable models for air-pollution forecasting. The key objectives of the study include: reviewing interpretable approaches and motivating explanation alongside predictive performance. The technology used includes interpretable machine-learning models and explainable AI methods. The methodology integrates: a systematic review and comparison of published approaches. The study ensures efficiency through: consolidating techniques that balance accuracy and interpretability. Despite its strengths, the study identifies challenges such as a lack of dataset-specific validation.

II.2 AI for Air-Pollution Monitoring and Forecasting

"Application of Artificial Intelligence in Air Pollution Monitoring and Forecasting" [2] and "A Systematic Scrutiny of AI-Based Air Pollution Prediction Techniques" [3] survey the data, models, and open challenges in the field. The key objectives include: summarizing methods and identifying challenges and viable solutions. The technology used includes machine-learning and deep-learning models. The methodology integrates systematic reviews. The studies ensure efficiency through structured comparison of techniques. Challenges include: broad scope, which limits direct evidence for a specific station or horizon.

II.3 SHAP: Unified Model Interpretation

Lundberg and Lee [4] propose SHAP, which explains individual predictions using Shapley-value concepts.

The key objective is consistent feature attribution. The technology is an additive feature-attribution method, including tree-based explainers. Efficiency: local and global explanations from one framework. Challenge: attributions describe model behaviour and not causal relationships. Research gap. The working gap is the integration of a reproducible, site-specific PM2.5 workflow with chronological evaluation, a mandatory persistence baseline, model explanations and a demonstration dashboard. Many studies report accuracy alone, without checking whether a model beats simply repeating the last observation. Data analytics, intelligent applications, and emerging technologies: The survey of driver-monitoring systems using computer vision [9] demonstrates the potential of visual intelligence for improving road safety and identifying driver-related risks, while the textbook on Python for data analytics [23] supports the application of programming and analytical techniques to data-driven problem-solving.

Machine-learning methods for malware detection [14] illustrate how predictive models can strengthen threat identification, and comparative implementations of password-authentication techniques [15] emphasize the importance of evaluating security mechanisms across programming environments. Research on quantum computing for supply logistics [16] highlights the potential of emerging computational paradigms to optimize complex logistics and supply-chain problems. Beyond cybersecurity, the survey of confidential-data protection in distributed cloud storage [17] reinforces the significance of privacy and data integrity, while soft clustering for gene-expression data [18] demonstrates the use of computational intelligence in biomedical analysis. Digital health and medical-tourism innovations [19] illustrate how digital technologies can support connected healthcare services, and research on ethics and regulations in AI-driven systems [20] underscores the importance of responsible AI deployment, governance, and patient protection.

III. PROPOSED SYSTEM DESIGN: AIR POLLUTION PREDICTION

The scientific rationale behind the proposed system is grounded in using supervised regression to forecast PM2.5 one hour ahead. Linear Regression provides a transparent baseline, while Random Forest captures nonlinear relationships between pollutants, meteorology and time. The system processes hourly observations from the Anand Vihar site: PM2.5, PM10, NO, NO_2, NO_x, NH_3, SO_2, CO, ozone, benzene, toluene, ambient temperature (AT), relative humidity (RH), wind speed (WS), wind direction (WD), rainfall (TOT-RF), solar radiation (SR), barometric pressure (BP), and the time features hour, day of week and month. The forecasting target is

$$\hat{y}_{t+1} = f(\mathbf{x}_t; \theta), \quad (1)$$

where $\mathbf{x}_t$ contains only information available at the forecast origin. A persistence baseline $\hat{y}_{t+1} = y_t$ is used to test whether the trained models show real skill, and SHAP-style feature contributions explain each prediction.

IV. ARCHITECTURE DIAGRAM: PREDICTION AND EXPLANATION PIPELINE

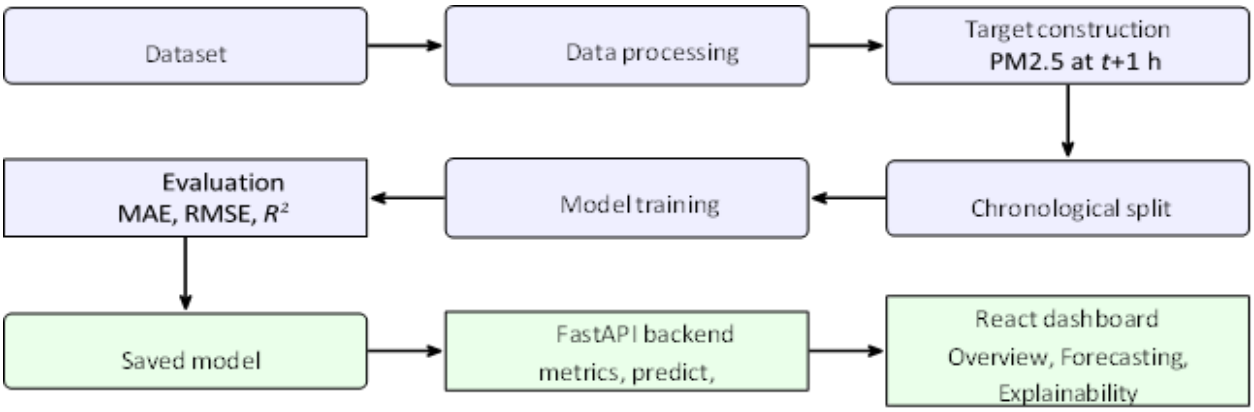


Figure 1: Architecture Diagram of AirInsight: An Explainable Air Pollution Prediction Platform

V. METHODOLOGY AND ALGORITHMS USED FOR AIR POLLUTION PREDICTION

The methodology involves multiple stages of data collection, preprocessing, target construction, model training, and performance evaluation. The system follows the structured workflow below:

- Data Collection: Hourly observations (14,345 rows; 13,981 usable one-hour steps) from the Anand Vihar, Delhi (DPCC) workbook, 1 January 2025 to 30 September 2026.
- Data Preprocessing: Sheets merged and column names standardised; timestamps parsed, sorted, and de-duplicated; all-missing columns and features with more than 50% missingness removed; negative PM2.5 treated as invalid; median imputation fitted on training data only.
- Feature and Target Construction: Time features (hour, day of week, month) added; the next record is used as the target only if it is exactly one hour later, so multi-hour gaps are never treated as one-hour forecasts.
- Model Training: Chronological 80%/20% split (2,797 test rows); Linear Regression (median imputation and standard scaling) and Random Forest (200 trees) are trained on the earlier period.
- Evaluation and Validation: MAE, RMSE and R^2 on the held-out later period, compared with a persistence baseline. AirInsight utilizes the following algorithms:
- Linear Regression: a transparent baseline that models the target as a weighted sum of standardised features.
- Random Forest Regressor: an ensemble of decision trees that captures nonlinear feature interactions.
- Persistence baseline: predicts that the next hour equals the current hour, used to judge real forecasting skill.
- Explainability (SHAP-style contributions): per-prediction and global mean absolute feature contributions describing model behaviour.

VI. PROJECT FUNCTIONAL MODULES IMPLEMENTATION: AIRINSIGHT

The development of AirInsight involves several functional modules: Data Processing Module: loading, cleaning, times-tamp auditing and target construction. Prediction Module: training and saving Linear Regression and Random Forest models, with a one-hour-ahead prediction for user-supplied inputs; empty fields are imputed with the training median. Evaluation Module: MAE, RMSE and R^2 with the persistence baseline on the chronological test set. Explainability Module: local per-prediction contributions and global feature influence, with CPCB band context stated as a research estimate and not an official AQI. Analytics & Visualization: interactive dashboard with dataset overview, weekly PM2.5 trend and actual-versus-predicted plots. Backend: FastAPI service with a React (Vite) frontend.

VII. METHODOLOGY FOR DEVELOPING THE AIRINSIGHT DASHBOARD SCREENSHOTS

Needs Assessment: Identify what users need from an air-quality forecasting tool (a clear forecast, error metrics, and reasons behind a prediction) and the limitations of black-box predictions. Requirement Definition: Define the essential features: dataset overview, model comparison against a baseline, next-hour prediction, and local and global explanations. Platform Design: Design an intuitive interface with three pages (Overview, Forecasting, Explainability) and interactive charts. Development: Implement the pipeline in Python (pandas, scikit-learn), save the model with joblib, serve it through FastAPI, and present it in a React front end. Testing: Evaluate models chronologically against the persistence baseline; check that dashboard values match the saved notebook outputs. Updating and Maintenance: Retrain periodically with new observations, add lagged features, and extend to other stations.

VIII. AIRINSIGHT PROTOTYPE, ALGORITHM, AND PROGRAM LOGIC

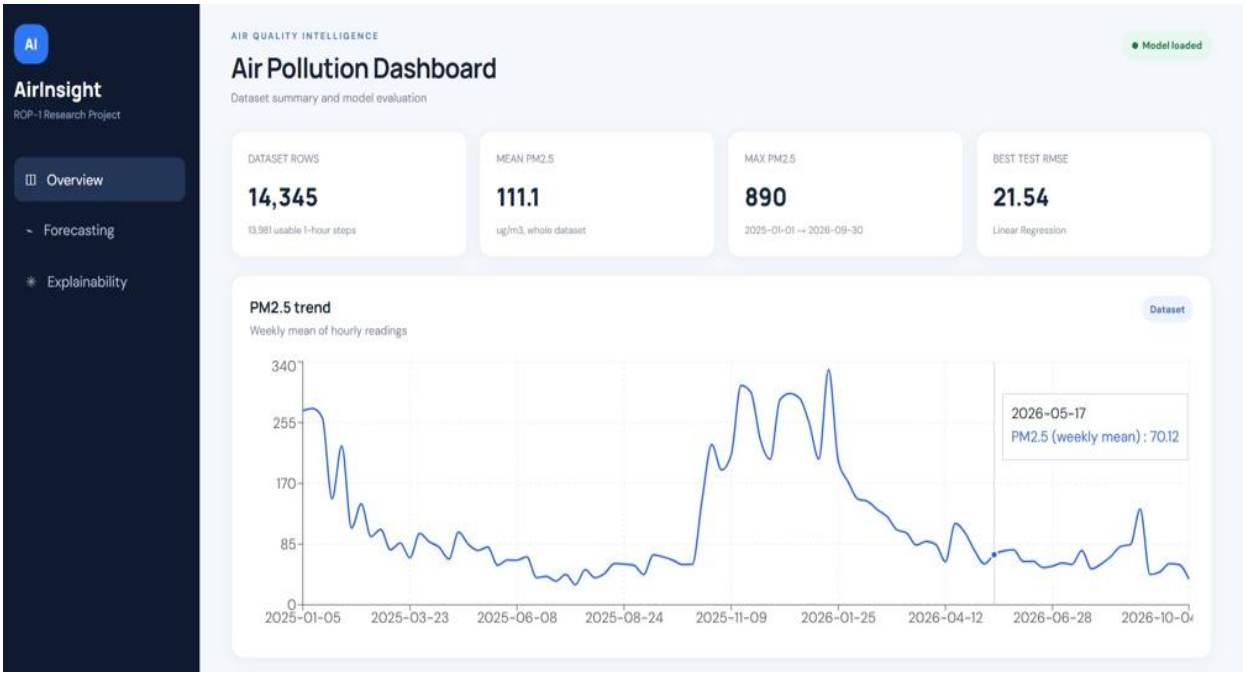


Figure 2: Figure 2: AirInsight Overview: dataset summary (14,345 rows, mean PM2.5 111.1 μg/m^3, maximum 890 μg/m^3) and weekly mean PM2.5 trend

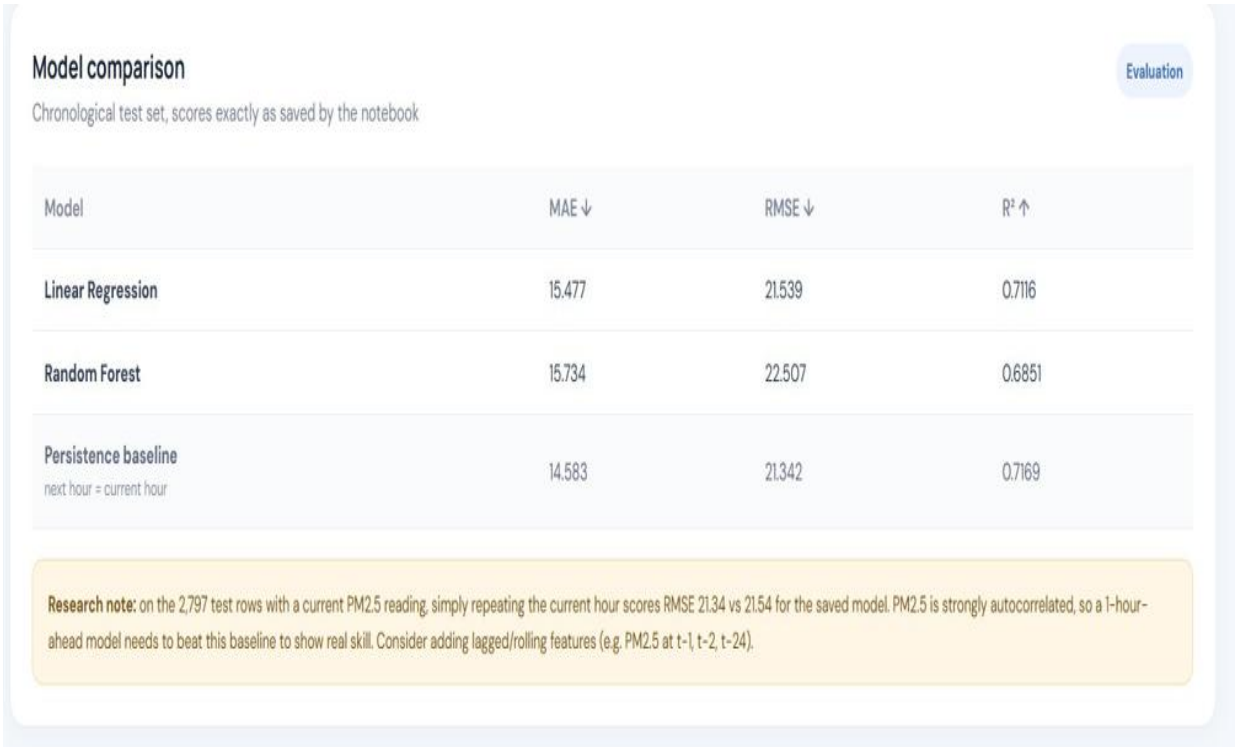


Figure 3: Figure 3: Model comparison with MAE, RMSE and R^2 on the chronological test set, including the persistence baseline

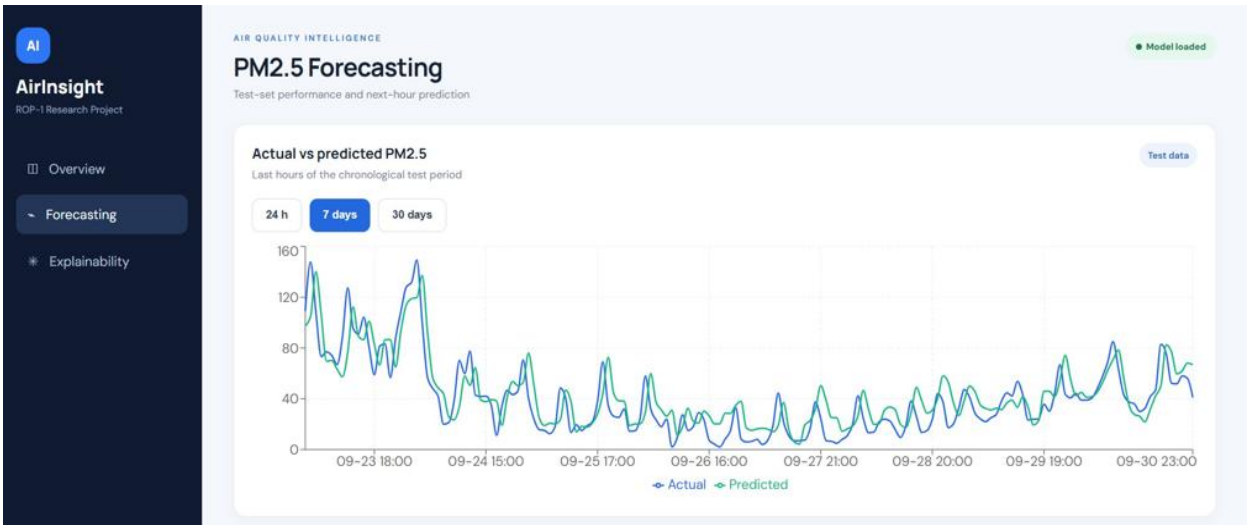


Figure 4: Figure 4: Actual versus predicted PM2.5 on the test data (7-day view)

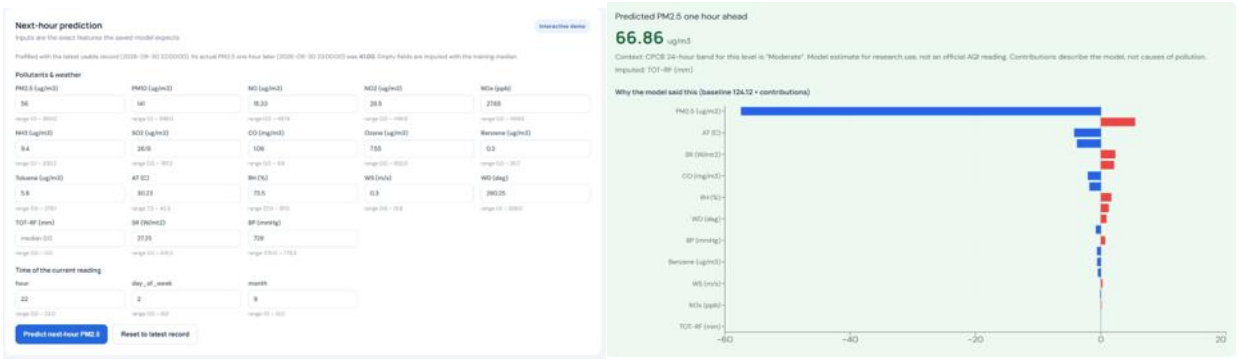


Figure 5: Figures 5 & 6: Next-hour prediction input form and prediction result (66.86 μg/m^3) with feature-contribution explanation

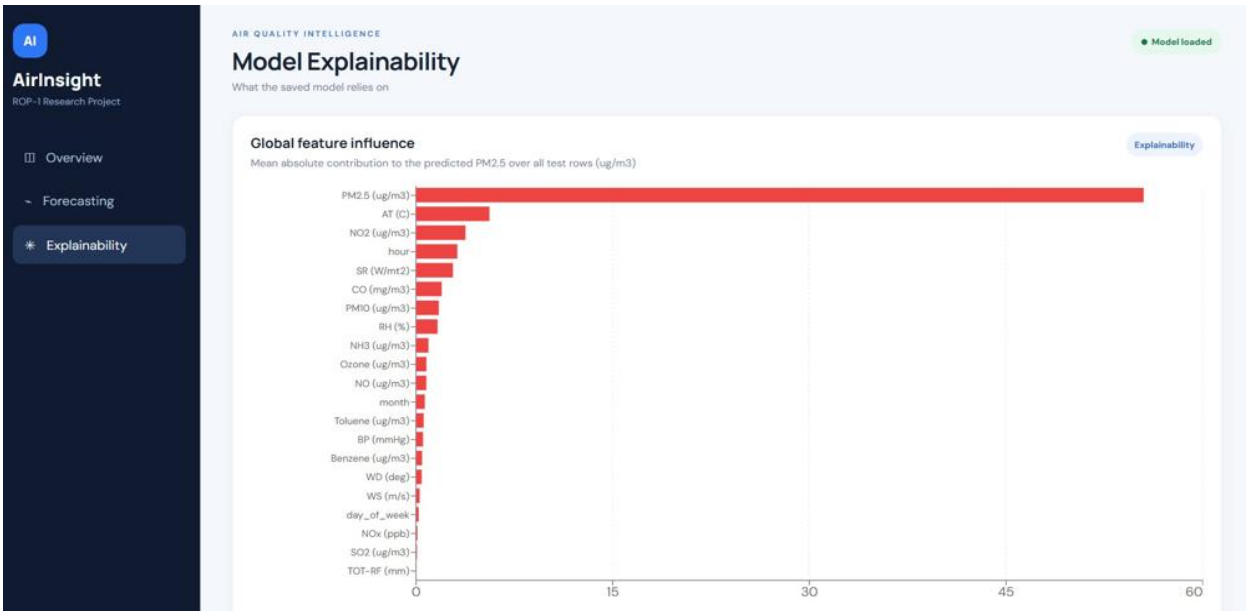


Figure 6: Figure 7: Global feature influence (mean absolute contribution over all test rows)

Program logic. The core of the forecasting pipeline (target construction and chronological evaluation) is shown below.

```
df["Future_PM25"] = df[TARGET].shift(-1)
gap = df["Timestamp"].shift(-1) - df["Timestamp"]
forecast_df = df[gap == pd.Timedelta(hours=1)].dropna(subset=["Future_PM25"])

split_idx = int(len(forecast_df) * 0.8)  # chronological split
X_train, X_test = X.iloc[:split_idx], X.iloc[split_idx:]
y_train, y_test = y.iloc[:split_idx], y.iloc[split_idx:]

for name, model in models.items():
model.fit(X_train, y_train)
pred = model.predict(X_test)
# MAE, RMSE, R2 computed on the held-out later period
```

IX. RESULTS AND DISCUSSION

Table 2: Chronological test-set performance for one-hour-ahead PM2.5

Model	MAE	RMSE	R^2
Linear Regression	15.477	21.539	0.7116
Random Forest	15.734	22.507	0.6851
Persistence baseline	14.583	21.342	0.7169

Linear Regression outperformed Random Forest on all three metrics, suggesting the next-hour relationship is largely linear and dominated by the current PM2.5 value. However, the persistence baseline scored slightly better than both trained models. Because PM2.5 is strongly autocorrelated, a one-hour-ahead model must beat this baseline to demonstrate real forecasting skill. The global explanation (Figure 7) agrees: current PM2.5 is by far the most influential feature, followed by temperature, NO_2, hour and solar radiation. These results apply to one site and one test period; contributions describe model behaviour and must not be read as causes of pollution.

X. CONTRIBUTION AND FINDINGS

The AirInsight project aims to provide a data-driven, transparent and user-friendly PM2.5 forecasting and explanation platform. By combining leakage-aware chronological evaluation, a persistence baseline, feature-contribution explanations, and an interactive dashboard, it demonstrates how explainable machine learning can be presented responsibly. The main finding is that, with current-hour features alone, simple models do not clearly beat persistence, which defines the direction of the next phase of work.

XI. CONCLUSION

The AirInsight platform presents a reproducible and explainable approach to PM2.5 prediction, integrating data preprocessing, one-hour-ahead forecasting, chronological model comparison, and SHAP-style explanations. Linear Regression performed best of the two trained models (RMSE 21.539, R^2 = 0.7116) but did not surpass the persistence baseline (RMSE 21.342). Moving forward, the integration of lagged and rolling features (PM2.5 at $t-1$, $t-2$, $t-24$), gradient boosting and LSTM models, longer forecast horizons, residual analysis, confidence intervals, and data from additional stations will further enhance the platform's effectiveness.

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