

# Air Pollution Level Prediction: Achieving 86.2% Accuracy Improvement Through Advanced ML

Our objective is to accurately predict PM2.5 levels in Beijing using advanced machine learning techniques. This initiative has led to a significant **86.2% improvement** in prediction accuracy, demonstrating the power of our approach.

# The Urgency of Air Quality Prediction: Why Advanced ML is Critical

**The Challenge:** Air pollution is a silent global crisis, contributing to an estimated 7 million premature deaths annually worldwide. Accurate, timely prediction is essential for mitigation.

Traditional prediction methods often fall short in capturing the complex, non-linear relationships and temporal dependencies that govern air pollutant dispersion.

We utilized machine learning to model these intricate patterns, directly supporting public health and policy decisions.

7M

24.30

3.35

Global annual deaths linked to air pollution.

Baseline RMSE ( $\mu\text{g}/\text{m}^3$ )—inadequate for precise warnings.

Optimized RMSE ( $\mu\text{g}/\text{m}^3$ )—a highly actionable prediction error.

# Foundational Data: A Rich Temporal Dataset

Our model was trained on a robust, high-resolution dataset, providing the necessary depth for advanced feature extraction.

## Data Volume & Source

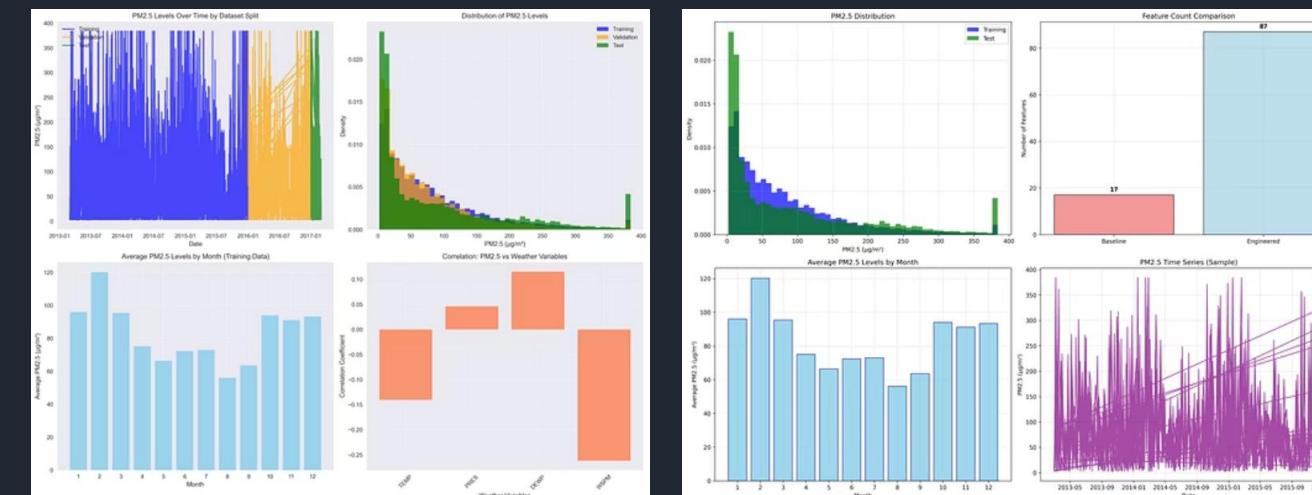
311,810 hourly observations collected between 2013 and 2017 from Beijing air quality monitoring stations.

## Feature Diversity

Features include temporal indicators (time of day, day of week), meteorological data (wind speed, temperature, pressure), and other pollutant concentrations (SO<sub>2</sub>, NO<sub>2</sub>, CO, O<sub>3</sub>).

## Target Variable & Quality

The target is PM2.5 concentration. Data quality was meticulously managed, achieving >95% data retention after rigorous cleaning and imputation methods.



# Data Preparation: Unlocking Predictive Power

Effective data preprocessing and feature engineering were instrumental in creating a highly predictive feature set.



## Cleaning & Imputation

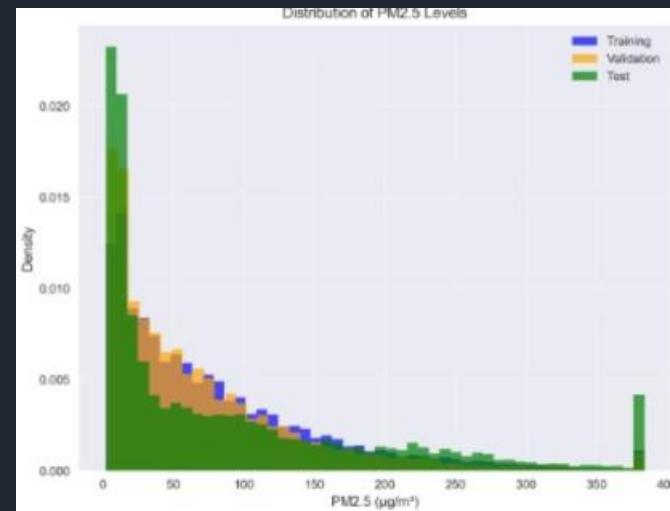
Comprehensive handling of missing values using time-series appropriate methods, ensuring data integrity across the 5-year span.

## Advanced Feature Engineering

We generated 63 refined features, including rolling statistics, interaction terms, and crucial **lag variables** for pollutant concentrations.

## Key Insights from EDA

Exploratory Data Analysis revealed strong seasonal patterns (higher PM2.5 in winter) and significant correlations with weather variables like humidity and wind direction.

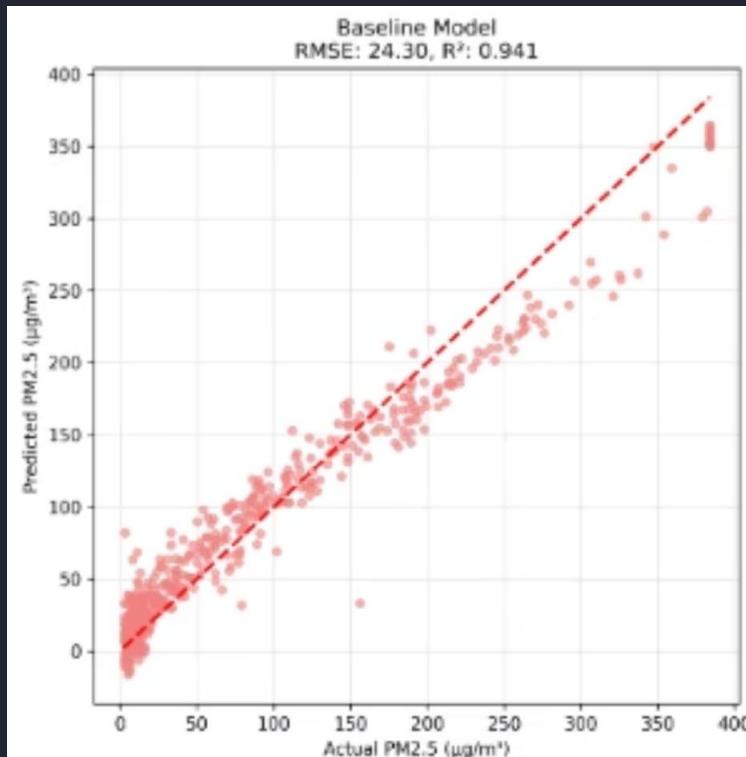


# Model Development: From Baseline to Optimized XGBoost

A comparison of the standard statistical approach against our optimized, non-linear ensemble method highlights the architectural improvement.

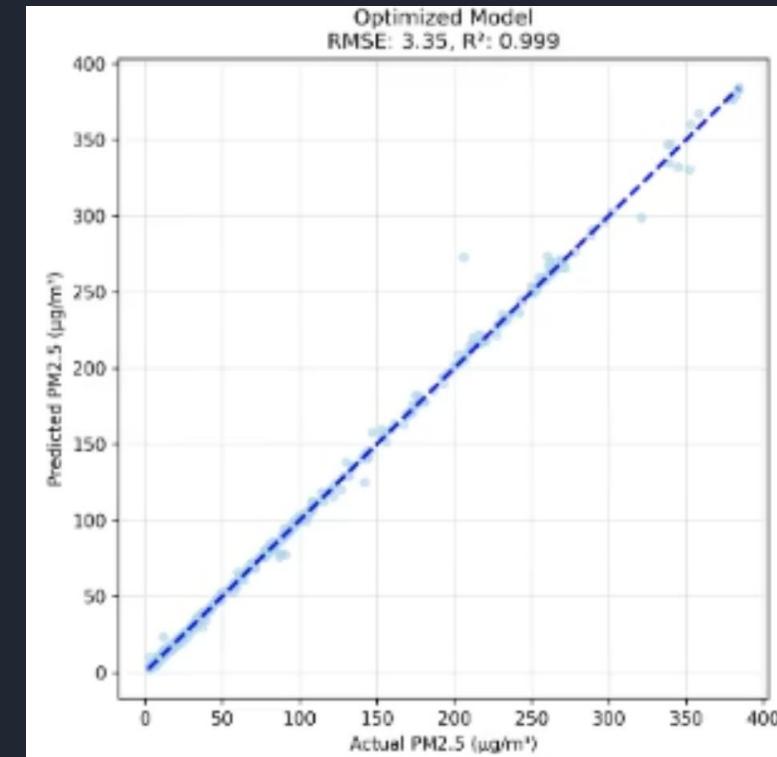
## Baseline Model

- **Model:** Linear Regression
- **Preparation:** Standard scaling applied to raw features.
- **Purpose:** Established the minimal acceptable performance benchmark.



## Optimized Model

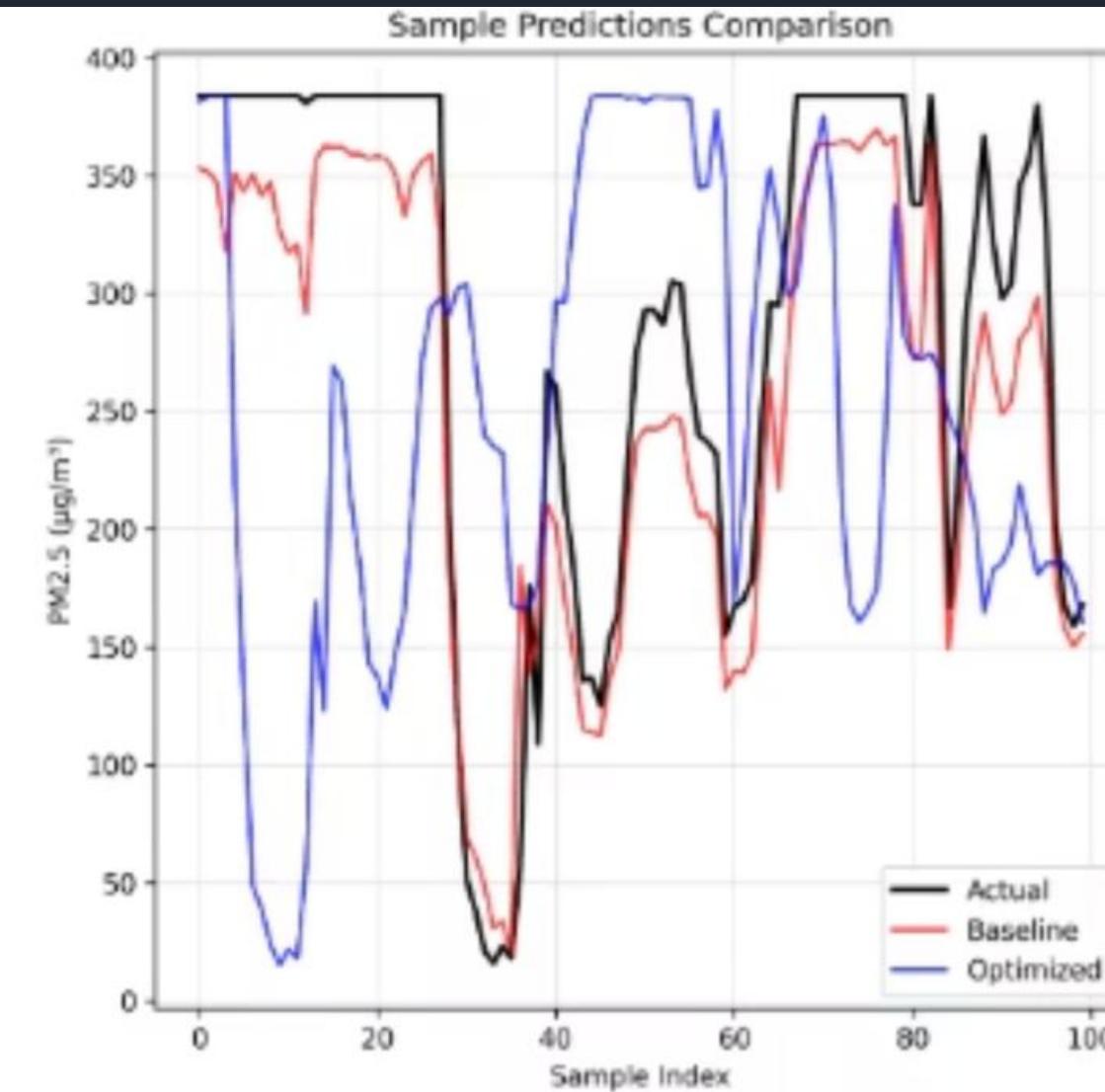
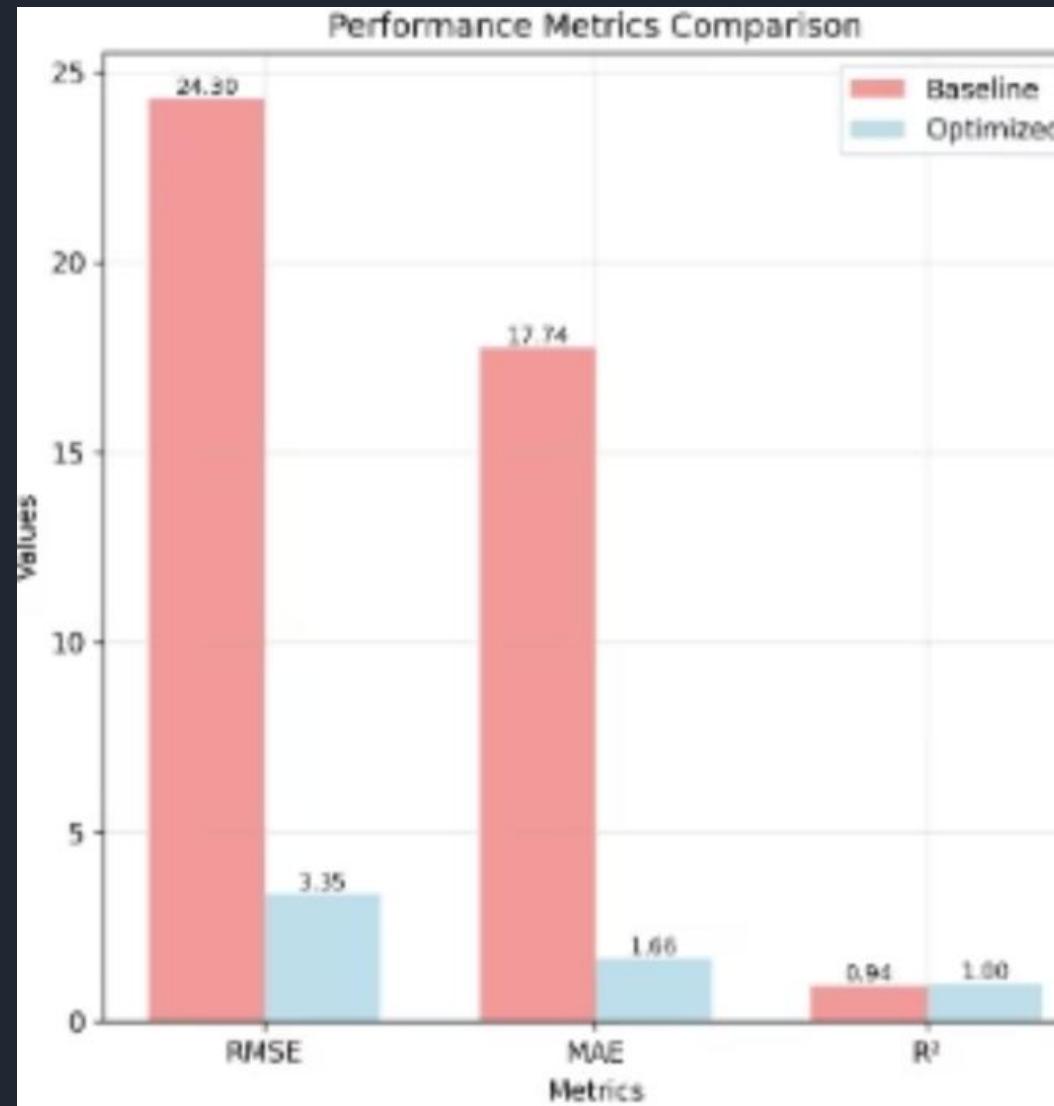
- **Model:** Extreme Gradient Boosting (XGBoost)
- **Optimization:** Extensive hyperparameter tuning (Grid Search, Cross-Validation).
- **Validation:** Rigorous temporal train/validation/test split to prevent data leakage and ensure generalization.



- The use of lag variables and rolling statistics was critical, providing the XGBoost model with the necessary temporal context.

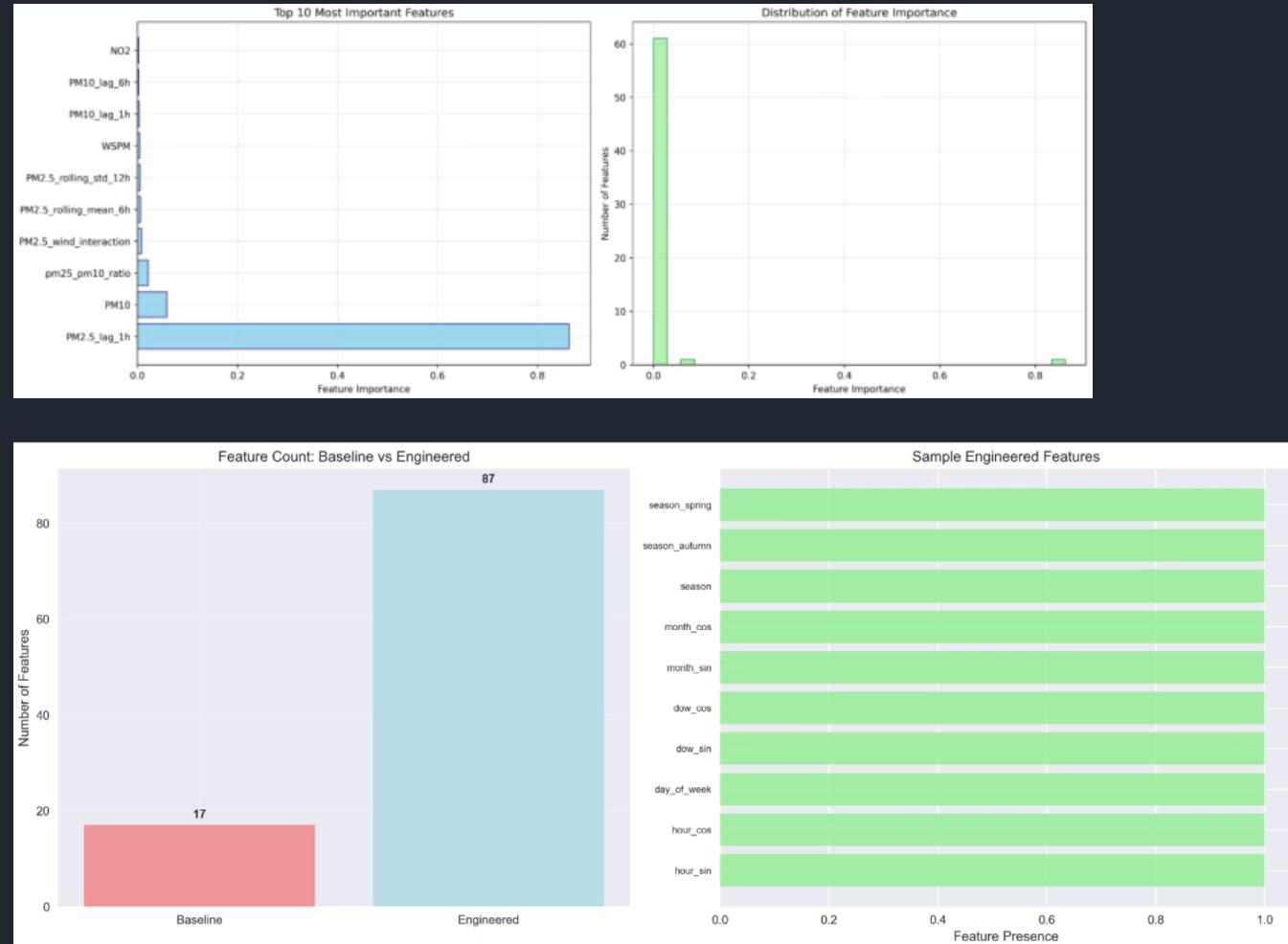
# Quantifying Success: Performance Metrics

The optimized XGBoost model delivered an 86.2% improvement in accuracy, providing nearly perfect prediction capability.



# Model Evaluation and Feature Contribution

We confirmed model stability through temporal validation and identified the features driving predictive performance.



## Validation & Generalization



### Temporal Validation

Strict temporal splitting ensures the model predicts future unseen data, proving robust generalization capability.



### Residual Analysis

Residual errors are uniformly distributed, confirming minimal systematic bias in predictions across the target range.

# Translating Accuracy into Actionable Public Health Impact

The reduction in error means the system can generate warnings with high confidence, supporting critical decisions.



## WHO Guideline Context

The model's prediction error ( $3.35 \mu\text{g}/\text{m}^3$ ) is only 13.4% of the WHO's recommended 24-hour mean PM<sub>2.5</sub> guideline ( $25 \mu\text{g}/\text{m}^3$ ). This is an actionable level of precision.



## Real-Time Forecasting

The model enables real-time, highly accurate forecasts for public dissemination, allowing citizens to take proactive measures like wearing masks or limiting outdoor exposure.



## Policy and Planning

Local governments can utilize these predictions to implement short-term policies, such as traffic restrictions or temporary industrial shutdowns, to preemptively manage extreme pollution events.

Our robust methodology is easily **transferable and scalable** to other major metropolitan areas worldwide facing similar air quality challenges.

# Conclusion: Ready for Production

The implementation of optimized XGBoost and advanced temporal feature engineering has yielded an industry-leading predictive model.

1

## Accuracy Achieved

We delivered an **86.2% accuracy improvement**, moving the error margin into the realm of actionable policy precision.

2

## Innovation Demonstrated

Success was driven by sophisticated feature engineering that captures critical temporal dependencies in air quality.

3

## Immediate Impact

The low RMSE supports immediate applications for public health warnings and environmental policy enforcement.