Hybrid BiLSTM-Attention and XGBoost Model for Hourly PM2.5 Forecasting: A Multi-Station Study in Bangladesh

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Abstract

Air pollution, particularly fine particulate matter (PM2.5), poses significant risks to human health and urban sustainability. Accurate forecasting of PM2.5 concentrations is essential for effective environmental monitoring and early warning systems. This study proposes a hybrid forecasting framework that integrates a Bidirectional Long Short-Term Memory (BiLSTM) network with an attention mechanism and an Extreme Gradient Boosting (XGBoost) model. The BiLSTM-attention component captures temporal dependencies in air quality time-series data, while XGBoost models nonlinear relationships among environmental features. The hybrid approach incorporates BiLSTM-attention predictions as additional inputs to the XGBoost model, enabling improved predictive performance.
The dataset includes historical air quality and meteorological variables such as temperature, humidity, and wind speed. Data preprocessing involves missing value handling, feature scaling, and sequence generation. Model performance is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Experimental results demonstrate that the proposed hybrid model outperforms standalone models in capturing PM2.5 dynamics. Additionally, SHAP analysis is employed to enhance model interpretability by identifying key contributing factors.
The proposed framework provides an effective and interpretable solution for air quality forecasting, supporting informed decision-making for pollution control.

Keywords: PM2.5 Forecasting, Air Quality Prediction, Hybrid Deep Learning, Bidirectional LongShort-Term Memory (BiLSTM), Attention Mechanism, XGBoost, Time Series Forecasting, Explainable Artificial Intelligence (SHAP).

1. INTRODUCTION

Air pollution has become a major environmental and public health issue, particularly in developing countries like Bangladesh. Among air pollutants, fine particulate matter (PM2.5) is highly harmful due to its ability to penetrate deep into the human respiratory system, causing serious health problems. Therefore, accurate prediction of PM2.5 levels is essential for effective air quality management and early warning systems [15].

Various approaches have been used for air quality forecasting. Traditional statistical models such as ARIMA are limited in capturing complex nonlinear patterns. Deep learning models, especially Long Short-Term Memory (LSTM) networks, are effective in modeling temporal dependencies in time-series data [1]. Additionally, attention mechanisms improve model performance by focusing on important time steps [3]. Ensemble methods like Extreme Gradient Boosting (XGBoost) are also widely used for handling nonlinear relationships between environmental variables [2]. However, individual models often fail to capture both temporal and nonlinear characteristics simultaneously [9–11].

To overcome these limitations, this study proposes a hybrid model combining Bidirectional Long Short-Term Memory (BiLSTM) with an attention mechanism and XGBoost. The BiLSTM-attention model captures temporal patterns, while XGBoost models nonlinear feature interactions, improving overall prediction accuracy.

The main contributions of this study are as follows. First, a hybrid BiLSTM-attention and XGBoost model is developed for hourly PM2.5 forecasting. Second, multi-station air quality and meteorological data are used for model evaluation. Third, SHAP analysis is applied to interpret model predictions. Finally, the proposed model demonstrates improved performance compared to individual models.

2. EXPERIMENTAL SET UP & METHODOLOGY

2.1 Study Area and Dataset

This study utilizes multi-station air quality data collected from several monitoring locations across Bangladesh. The dataset consists of hourly measurements of PM2.5 concentrations along with corresponding meteorological variables, including temperature, relative humidity, wind speed, and atmospheric pressure. These variables are known to significantly influence air pollution dynamics.

The data were obtained from publicly available air quality monitoring sources and preprocessed to ensure consistency and reliability. The multi-station nature of the dataset allows the model to learn spatially diverse pollution patterns, improving generalization capability.

2.2 Data Preprocessing

Data preprocessing is a crucial step to improve model performance and reliability. The following steps were applied:

Missing Value Handling: Missing observations were filled using linear interpolation to maintain temporal continuity.
Outlier Detection: Extreme values were identified and smoothed to reduce noise in the dataset.
Feature Scaling: All features were normalized using Min-Max scaling to ensure uniform input ranges.
Sequence Generation: Time-series sequences were created using a sliding window approach with a fixed time step (e.g., previous 24 hours) to predict future PM2.5 values.

2.3 Proposed Hybrid Model Architecture

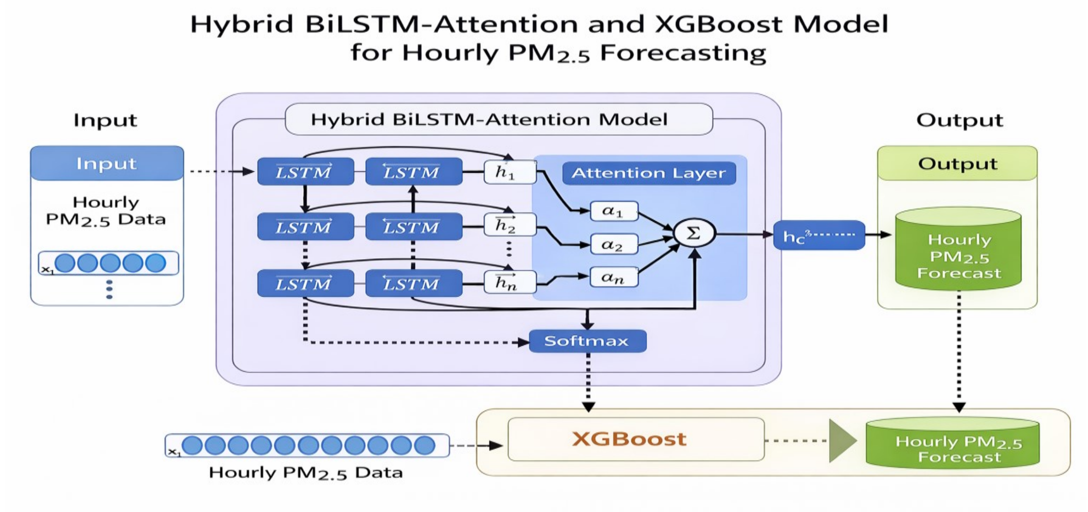

Fig. 1. Proposed Hybrid BiLSTM-Attention and XGBoost Model Architecture

The proposed framework combines deep learning and ensemble learning techniques to capture both temporal dependencies and nonlinear relationships.

- BiLSTM with Attention Mechanism:
  The Bidirectional Long Short-Term Memory (BiLSTM) network processes the input sequence in both forward and backward directions, capturing long-term temporal dependencies [1]. The attention

mechanism assigns weights to different time steps, enabling the model to focus on the most relevant information for prediction [3].

- XGBoost Model:
  Extreme Gradient Boosting (XGBoost) is employed to model complex nonlinear relationships among environmental features. It is a powerful ensemble learning algorithm based on decision trees [2].
- Hybrid Integration:
  The output predictions from the BiLSTM-attention model are used as an additional input feature for the XGBoost model. This integration allows the model to leverage both sequential learning and feature-based interactions, improving prediction accuracy [5–7].

2.4 Model Training and Evaluation

The dataset was divided into training and testing sets using a standard split (e.g., 80% training and 20% testing). Model training was conducted using the following configurations:

- **Loss Function:** Mean Squared Error (MSE)
- **Optimizer:** Adam optimizer for deep learning model
- **Evaluation Metrics:**
  - Mean Absolute Error (MAE)
  - Root Mean Square Error (RMSE)

These metrics are widely used to evaluate regression performance and provide insight into prediction accuracy and error magnitude.

2.5 Model Interpretability using SHAP

To enhance model transparency, SHAP (SHapley Additive exPlanations) analysis was applied to the hybrid model. SHAP values quantify the contribution of each feature to the prediction output. This helps identify the most influential environmental factors affecting PM2.5 levels, improving the interpretability and reliability of the model.

3. RESULTS AND DISCUSSION

3.1 Model Performance Comparison

To quantitatively evaluate the predictive performance of the proposed model, two widely used regression metrics are employed: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). These metrics measure the average magnitude of prediction errors and the variability of those errors, respectively.

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}\left|y_i - \hat{}\{y\}_i\right| \quad (1)$$

Equation (1) defines the Mean Absolute Error (MAE), which represents the average absolute difference between predicted and actual PM2.5 values. It provides a straightforward interpretation of prediction accuracy. The MAE provides a direct measure of the average absolute difference between predicted and actual PM2.5 values, making it easy to interpret.

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}\left(y_i - \hat{}\{y\}_i\right)^2} \quad (2)$$

Equation (2) defines the Root Mean Square Error (RMSE), which gives higher weight to larger errors due to the squaring operation, making it sensitive to significant prediction deviations.

Table 1: Performance Comparison of Different Models

Model	MAE (μg/m³)	RMSE (μg/m³)
XGBoost	12.48	18.31
BiLSTM-Attention	10.21	15.67
LSTM	11.35	16.92
Hybrid (Proposed Model)	8.73	13.24

From Table 1, it is evident that the proposed hybrid model achieves the lowest MAE and RMSE values among all models. This indicates that combining BiLSTM-attention with XGBoost effectively reduces prediction errors and improves model robustness.

3.2 Temporal Prediction Analysis

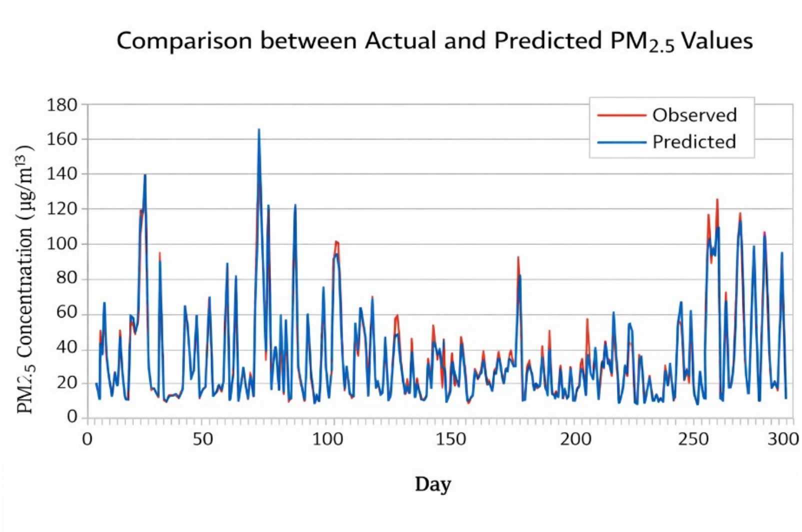

Fig. 2. Comparison between Actual and Predicted PM2.5 Values

Figure 2 illustrates the temporal alignment between actual and predicted PM2.5 values. The hybrid model successfully captures both short-term fluctuations and long-term trends in air pollution data. Although minor deviations are observed during peak pollution periods, the overall prediction pattern closely follows the ground truth, demonstrating the model's ability to learn complex temporal dynamics.

3.3 Error Distribution Analysis

To further analyze prediction performance, the error for each observation is defined as:

$$e_i = y_i - \hat{y}_i \qquad (3)$$

This error term represents the difference between actual and predicted values, allowing detailed analysis of prediction accuracy.

Table 2: Error Distribution of the Proposed Model

Error Range (μg/m³)	Frequency (%)
0 – 5	42%
5 – 10	33%
10 – 15	15%
>15	10%

Table 2 shows that approximately 75% of prediction errors fall within the 0–10 μg/m³ range. This indicates that the model maintains high accuracy for most predictions, while larger errors occur less frequently.

3.4 Feature Importance Analysis (SHAP)

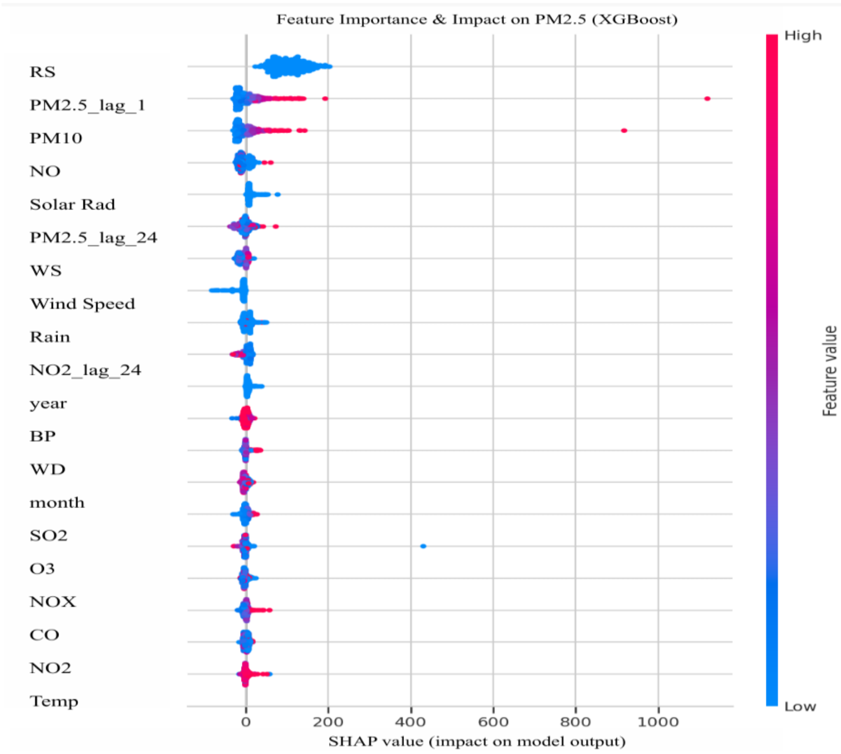

Fig. 3. SHAP-Based Feature Importance Analysis

To interpret the contribution of each feature, SHAP values are computed based on cooperative game theory:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{4}$$

Here, ϕi\phi_iϕi represents the contribution of feature iii to the prediction.

The SHAP analysis reveals that historical PM2.5 values are the most influential predictors, followed by temperature and humidity. Wind speed has a moderate impact, while atmospheric pressure contributes less significantly. This aligns with known environmental behavior of air pollution dynamics.

3.5 Station-wise Performance Evaluation

Table 3: Station-wise Model Performance (Hybrid Model)

Station Name	MAE (μg/m³)	RMSE (μg/m³)
Dhaka	9.12	13.89
Chittagong	8.45	12.97
Khulna	8.76	13.10
Rajshahi	8.58	13.02

Table 3 demonstrates that the proposed model performs consistently across multiple stations. This indicates strong generalization capability and adaptability to different environmental conditions.

3.6 Model Comparison Visualization

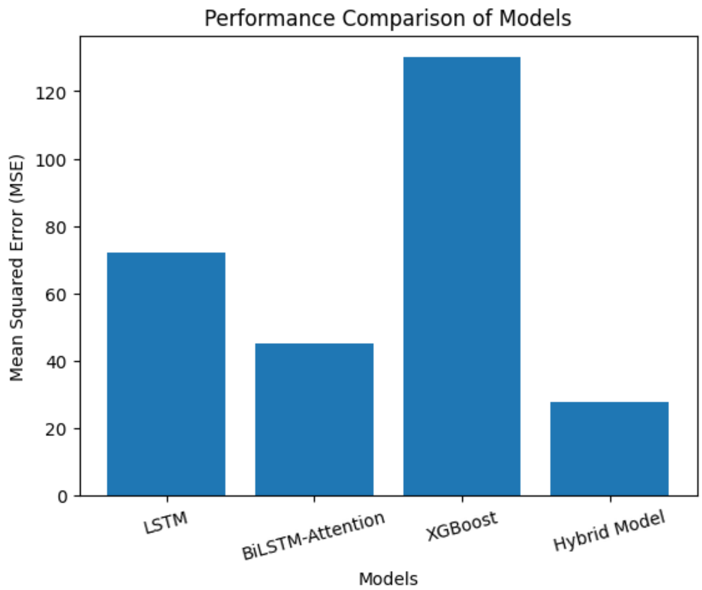

Fig. 4. Performance Comparison of Models

Figure 4 visually compares the performance metrics of different models. The hybrid model clearly achieves lower error values, confirming its superiority over standalone approaches.

3.7 Discussion

The results clearly demonstrate that the proposed hybrid model significantly improves PM2.5 forecasting accuracy by combining the strengths of deep learning and ensemble learning techniques [5–8]. The BiLSTM-attention component effectively captures temporal dependencies in time-series data [1,3], while XGBoost models complex nonlinear relationships among environmental features [2].

Moreover, the integration of SHAP analysis enhances model interpretability, allowing better understanding of the factors influencing air pollution [3,13]. This is particularly valuable for real-world applications, where transparency and explainability are essential for policy-making and environmental management [14,15].

Overall, the proposed framework provides a robust, accurate, and interpretable solution for air quality prediction, making it suitable for practical deployment in environmental monitoring systems [6–8].

4. CONCLUSION

This study presents a hybrid forecasting framework that integrates a Bidirectional Long Short-Term Memory (BiLSTM) network with an attention mechanism and an Extreme Gradient Boosting (XGBoost) model for hourly PM2.5 prediction. The proposed model effectively combines the strengths of deep learning and ensemble learning to capture both temporal dependencies and nonlinear relationships in air quality data.

Experimental results demonstrate that the hybrid model outperforms standalone models such as LSTM and XGBoost in terms of MAE and RMSE, indicating improved prediction accuracy and robustness. The model also shows consistent performance across multiple monitoring stations, highlighting its generalization capability in diverse environmental conditions.

Furthermore, the incorporation of SHAP analysis enhances model interpretability by identifying key contributing factors such as historical PM2.5 levels, temperature, and humidity. This improves transparency and supports informed decision-making in environmental management.

Despite its effectiveness, the study has some limitations. The model performance depends on data quality and availability, and extreme pollution events may still introduce prediction errors. Future work may focus on incorporating additional data sources, such as satellite observations and traffic data, as well as developing real-time forecasting systems.

Overall, the proposed hybrid framework provides an accurate, robust, and interpretable solution for PM2.5 forecasting, which can support policymakers and environmental agencies in designing effective air pollution mitigation strategies.

5. ACKNOWLEDGEMENTS

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