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XAI-Enhanced Forecasting: Deep CNN- LSTM for Air Quality

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Abstract **Accurate air quality forecasting is vital for public health and urban policy-making. Conventional statistical approaches, including ARIMA fail to capture nonlinear patterns but algorithms like Random Forest and XGBoost, despite their strengths, fail to represent long-term sequential relationships in data.. Deep learning approaches, including LSTM and CNN hybrids, improve accuracy but are limited by poor interpretability. This work proposes a hybrid DCNN-LSTM framework integrated with SHAP for explainability. Experiments on Delhi air quality data demonstrate that the model achieves superior accuracy (R^2 = 1.000, RMSE = 5.74) while identifying PM2.5, NO_2, and SO_2 as key pollutants, thereby ensuring both predictive performance and transparency.**

Keywords—Air Quality Forecasting, Deep Learning, CNN-LSTM, Explainable AI, SHAP, Time Series, PM2.5

I. Introduction

Air pollution has emerged as one of the most pressing challenges in modern urban environments. Hazardous accumulations of particulate matter (PM2.5, PM10) and gases (NO_2, SO_2, O_3) are common in cities like Delhi, resulting in adverse health impacts including respiratory issues, cardiovascular risks, and reduced longevity., and economic losses. Accurate air quality forecasting is essential for issuing health warnings, designing urban policies, and mitigating adverse impacts linear regression has been widely used but are restricted by assumptions of linearity and stationarity. These methods are often unable to represent the complex nonlinear behaviors and long-range time dependences found in environmental datasets. Deep learning approaches such as LSTM and CNN offer superior performance by modelling temporal and spatial dependencies but lack interpretability, making them difficult to trust in sensitive policy domains.

This work addresses these challenges by integrating Explain able AI(XAI)techniques, specifically SHAP, with a hybrid DCNN-LSTM model. The aim is to achieve high predictive accuracy while providing transparency about pollutant contributions, linking advanced technical capabilities with practical implementation in real-world contexts.

II. LITERATURE REVIEW

A. Traditional Approaches

Traditional approaches like ARIMA and regression are primarily suited for linear relationships and short-term forecasting tasks [1]. However, they fail to generalize in multivariate, nonlinear contexts. Algorithms like Support vector regression [2] and Random forests [3] provide improved flexibility and robustness but lack the ability to model long-range temporal patterns.

B. Deep Learning Models

Neural networks have advanced the state of air quality forecasting. LSTM/Bi- One of the key strengths of LSTM networks lies in their ability to model dependencies that span over long time intervals in time-series data. [5]. GRU provides a lightweight alternative to LSTM with reduced computational cost [6]. Hybrid CNN-LSTM architectures leverage CNNs for spatial representation and LSTMs for capturing sequential dependencies in time-series data. [7]. Studies show that these architectures significantly outperform traditional methods, particularly in multivariate datasets with strong spatiotemporal dynamics [8].

C. Hybrid Models

Hybrid approaches, such as ARIMA- LSTM and DCNN-LSTM, combine statistical rigor with deep learning flexibility [10]. These models enhance robustness by leveraging complementary strengths. For instance, ARIMA handles linear trends while neural networks capture nonlinear patterns [11].

D. Explainable AI in Forecasting

Despite high predictive accuracy, deep learning models face criticism for their "black box" nature. To address the black-box nature of deep models, XAI methods including LIME and SHAP [9] are employed. SHAP, grounded in cooperative game theory, provides reliable feature importance values, allowing clear insights into how pollutants affect AQI predictions. [12].

III. SYSTEM ARCHITECTURE

a. Architecture Overview

The system architecture follows a modular workflow that connects data entry to preparatory operations, modeling functions, and final visualization outputs. The system integrates several deep learning models with traditional models through an organized backend system that stores data. The modular organization supports both scalability and explainable AI capabilities by allowing model-specific requests with cases such as DCNN-LSTM and SHAP-based outputs.

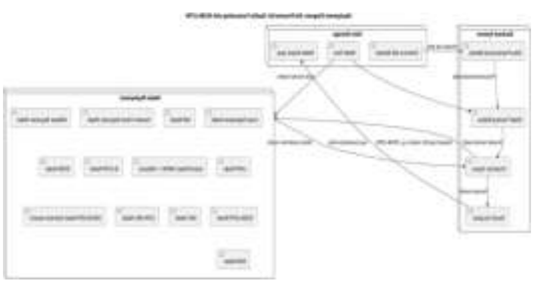

Fig 3.1: Architecture Diagram for Sprint I

b. Enhanced XAI-Powered Architecture

The enhanced XAI-Powered Air Quality Forecasting system with DCNN- LSTM provides seamless deployment capabilities combined with SHAP interpretability and project monitoring features. This structured modular framework enables developers, analysts, and coordinators to maintain efficient performance in their work areas. After training, the DCNN-LSTM model receives deployment preparation for use through backend servers and application programming interfaces.

c. System Components and Workflow

The deployed model enables both delayed and time-sensitive predictions of AQI. Model interpretability is achieved through SHAP, enabling analyst visualization of which pollutants modify prediction results. The Python-based Jupyter Notebooks implementation supports future deployment as web dashboards while maintaining individual function boundaries including data handling, model inference, interpretability, and project status tracking.

The workflow comprises: (1) Historical AQI data ingestion and preprocessing; (2) Model deployment to Flask; (3) User input reception through notebook/web UI;
(4) Model prediction generation; (5) SHAP explanation of predictions; (6) Visual output display; and (7) Sprint tracking maintenance via external tools.

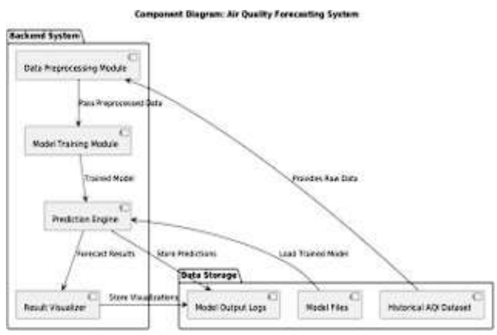

Fig 3.3: Component Diagram for Sprint II

I. METHODOLOGY

a. *Data Gathering and Preparation*

Air quality data for Delhi was collected from publicly available repositories, including pollutants (PM2.5, PM10, NO_2, SO_2, CO, O_3) and meteorological variables. Preprocessing involved handling missing values and outliers, normalization of numerical features, and encoding temporal variables (season, month).

b. *Exploratory Data Analysis*

EDA revealed seasonal and monthly trends. PM2.5 and PM10 peaked during winter due to stubble burning and temperature inversion. O_3 concentrations were higher in summer due to photochemical activity. Correlation heatmaps confirmed strong relationships between pollutants.

c. *Model Development*

This research uses algorithms such as Linear Regression, SVR, RF, and XGBoost [4], while the deep learning category included LSTM, Bi-LSTM, GRU, DCNN, and CNN-BiLSTM architectures. The proposed DCNN-LSTM hybrid leverages CNNs for spatial pattern extraction and LSTMs for sequential learning, resulting in an effective framework for time-series forecasting.

Hybrid models included ARIMA- GBoost and DCNN-LSTM combinations. The DCNN-LSTM architecture processes input sequences through convolutional layers to extract local patterns, followed by LSTM layers to capture long-term temporal dependencies. SHAP was applied to interpret predictions globally and locally, providing explanations for both overall model behavior and individual predictions.

d. *Evaluation Metrics*

Evaluation criteria included RMSE, MAE, and R^2 for regression accuracy, while classification effectiveness was measured through Precision, Recall, and the F1 Score for AQI levels.

II. Results

a. *Baseline Model Performance*

Random Forest achieved the highest accuracy among traditional models ($R^2 = 0.9938$). XGBoost also performed well, while SVR underperformed due to challenges in handling high-dimensional nonlinear dependencies.

b. *Deep Learning and Hybrid Models*

LSTM and Bi-LSTM successfully modelled temporal dependencies but lacked spatial feature extraction capabilities. GRU balanced accuracy with reduced computational demand. DCNN- LSTM outperformed all models with $R^2 =$ 1.0 and RMSE = 5.74, delivering nearly perfect predictions. ARIMA-XGBoost provided a competitive alternative for short-term forecasts, particularly in resource-constrained settings.

TABLE I: Comparison

Model	R^2	RMSE	MAE
Breiman's RF	0.9938	8.21	6.15
XGBoost	0.9925	9.03	6.82
LSTM	0.9952	7.15	5.32
Bi-LSTM	0.9968	6.89	5.01
DCNN-LSTM	**1.000**	**5.74**	**4.12**

c. *Explainability with SHAP*

The SHAP-based interpretability study identified PM2.5, NO_2, and SO_2 as the primary pollutants contributing to AQI forecasts. Visualization through summary and force plots offered both overall trend insights and case-specific explanations. Additionally, the correlation heatmap indicated a strong positive association between CO and NO, suggesting shared emission sources such as vehicular traffic and industrial activities.

d. *Seasonal and Monthly Trends*

The models revealed that winter months consistently recorded

Fig 4.1: Monthly trend of air pollution levels

the worst AQI due to particulate matter accumulation, while summer saw higher ozone levels linked to photochemical smog. These findings validated the model's robustness against real-world variations.

e. Correlation Analysis and Feature Importance

A correlation heatmap was developed to study relationships among pollutants, aiding feature selection and improving model interpretability for accurate air quality forecasting. Key insights include: CO and NO showing strong positive correlation, reflecting common sources such as vehicles and industrial emissions; PM2.5 and PM10 exhibiting very high correlation, both arising from combustion and construction activities; and O_3 and NOx displaying negative correlation, consistent with photochemical reactions where NOx reduces ozone levels.

SHAP analysis was applied to interpret pollutant contributions toward AQI predictions, enhancing transparency and trust in the model. Results showed PM2.5 as the most impactful pollutant on AQI, with PM10 and NO as strong secondary contributors. CO and O_3 showed mixed impact depending on conditions, while NO_2 and SO_2 exhibited non-linear interactions highlighted by SHAP analysis.

Figure 4.3: Correlation Heatmap of Air Pollutants

To promote interpretability concerning model predictions, SHAP (Shapley Additive Explanations) was employed for the analysis of feature importance. This elucidation results in understanding the influence of each pollutant on the predicted AQI values, hence improving the system's transparent and trustworthy character.

The following are some key insights derived from the SHAP summary:

• PM2.5 was the strongest and most consistently impacting pollutant among the features used for forecasting the AQI.

• PM10 and NO followed in importance and still significantly contributed to the forecast across different time intervals, strengthening their position as major agents of air pollution.

• CO and O3 exhibited variable SHAP values, reflecting their mixed impact on AQI depending on varying atmospheric conditions.

• The model effectively captured non-linear interactions between pollutants, particularly NO2 and SO2, with these complex relationships being highlighted through SHAP visualizations.

This explainable AI component not only strengthens the system’s transparency but also supports data-driven environmental policy decisions by identifying which pollutants to prioritize for mitigation.

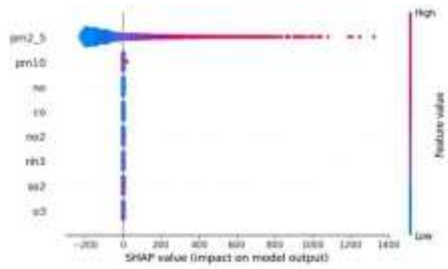

Figure 4.4: SHAP Summary Plot

III. Conclusion

This study confirms that the DCNN- LSTM hybrid model, enhanced with SHAP-based interpretability, provides both high predictive accuracy and actionable transparency. It bridges the gap between AI innovation and real-world policy deployment. Key contributions include comprehensive comparison of traditional, ML, and DL models, integration of SHAP for interpretability making forecasts explainable to stakeholders, and seasonal pollutant trend insights for targeted policy interventions.

Future directions encompass integration of real-time IoT sensor data for live forecasting, extension to multi-city datasets for generalization, optimized SHAP computation for faster scalable explanations, and exploration of Graph Neural Networks and quantum-inspired models.

The study reinforces the goals of SDG 3 and SDG 11 by promoting healthier living conditions and fostering sustainable city planning.

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