AI-Driven Multisource Data Fusion for Real-Time Urban Air Quality Forecasting and Health Risk Assessment

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***Abstract*—Air pollution has emerged as a pressing challenge in rapidly urbanizing regions, demanding accurate and timely forecasting solutions to mitigate its adverse health impacts. This study presents a comprehensive AI-driven framework that integrates multisource environmental data—comprising satellite imagery, ground-level sensors, meteorological inputs, and mobile IoT devices—for enhanced air quality forecasting in urban settings. Leveraging advanced deep learning models, particularly LSTM and Transformer-based architectures, the system captures complex spatio-temporal patterns in pollutant behavior. A key innovation of this work lies in its data fusion strategy, which synchronizes heterogeneous data streams to improve prediction reliability. Furthermore, the model incorporates a health risk assessment module that translates pollutant forecasts into actionable health indicators based on population demographics and WHO-defined exposure thresholds. Experimental results across multiple urban zones demonstrate significant improvements in predictive accuracy when compared to traditional statistical models, with RMSE reductions exceeding 20%. The system also offers real-time responsiveness through edge-enabled deployment, ensuring low latency in high-density urban environments. By bridging the gap between environmental sensing and public health analytics, this work contributes to smarter urban planning, policy intervention, and personalized health alerts. The proposed approach not only advances the technological frontiers of air quality monitoring but also provides a scalable model for integration within smart city ecosystems.**

***Keywords*—Air Quality Forecasting, Multisource Data Fusion, Health Risk Assessment, Smart City, Edge Computing.**

I. INTRODUCTION

Air quality has become a central public health and environmental concern due to rapid urbanization, industrial growth, and increasing vehicular emissions in metropolitan regions across the globe. Poor air quality is directly linked to a rise in respiratory and cardiovascular ailments, premature mortality, and diminished quality of life [1], [2]. Traditional air quality monitoring systems primarily depend on static ground-based stations that are often sparsely distributed and limited in temporal granularity. Such limitations restrict the ability to capture localized pollution variations in real time and hinder effective policy response or individual health risk mitigation [3], [4].

Conventional statistical models for Air Quality Index (AQI) forecasting, such as ARIMA or simple regression models, often fall short in capturing the non-linear and dynamic nature of air pollution behavior influenced by diverse environmental and anthropogenic factors [5]. Additionally, most existing frameworks focus on single-source datasets—either ground sensors or meteorological inputs—neglecting the potential synergy of multisource data integration [6]. These models often lack adaptability to real-time environmental changes and cannot be efficiently scaled for smart city applications requiring low-latency decision-making.

To address these challenges, this research proposes an AI-powered framework for real-time urban air quality forecasting that utilizes a fusion of heterogeneous environmental data sources. Specifically, the system incorporates inputs from ground-level pollution sensors, meteorological data streams, satellite-based aerosol observations (e.g., Sentinel-5P), and mobile IoT devices [7], [8]. By employing deep learning models, particularly Long Short-Term Memory (LSTM) networks and Transformer-based spatio-temporal models, the framework captures intricate patterns and dependencies in air quality dynamics across both space and time [9], [42].

A distinctive component of the proposed system is its integration of a health risk assessment module that maps predicted pollutant concentrations to health impact levels, using exposure thresholds defined by global health agencies such as the WHO [11]. This component considers population density, age distribution, and historical morbidity data to provide area-specific health alerts and risk scores [47].

The key contributions of this paper are as follows:

- A novel multisource data fusion architecture combining IoT sensor readings, meteorological data, and satellite imagery for enriched AQI prediction.
- Deployment of advanced AI models that outperform traditional methods in terms of forecasting accuracy and spatio-temporal adaptability.
- A health risk quantification layer that interprets AI outputs into actionable health insights.
- Edge-compatible smart city deployment, enabling real-time air quality alerts for policy makers, urban planners, and the general public.

Fig. 1 illustrates the proposed system architecture. The fusion layer aggregates and synchronizes data from diverse sources, which is then fed into AI models for prediction. The forecasting results trigger the health risk assessment module, with outputs displayed on a user dashboard and public portals.

The remainder of this paper is organized as follows: Section II reviews related work, Section III details the proposed methodology, Section IV presents experimental results and evaluation, and Section V concludes with future research directions.

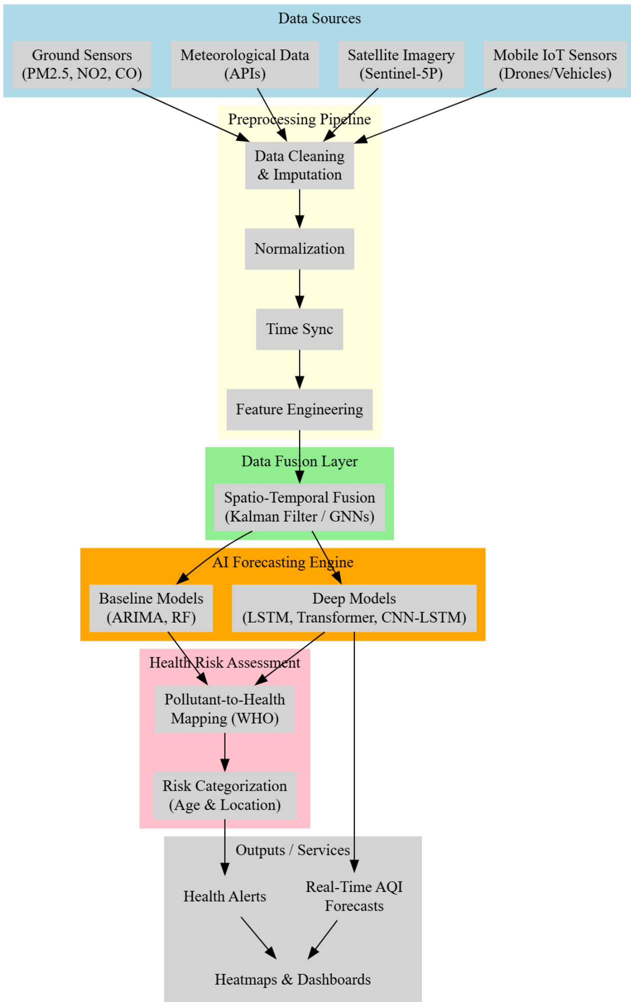

Fig. 1: System architecture for multisource AI-based AQI forecasting and health risk assessment

II. Related Work

The challenge of accurately forecasting air quality has been extensively explored through both traditional statistical models and modern AI-based techniques. Historically, methods such as AutoRegressive Integrated Moving Average (ARIMA), Multiple Linear Regression (MLR), and Kalman Filtering have been widely used for Air Quality Index (AQI) prediction [41], [43], [18]. While these approaches are computationally efficient, they often fall short in modeling the nonlinear and spatio-temporal dynamics of pollutant dispersion, especially under changing meteorological conditions [19].

With the rise of data-driven methodologies, machine learning (ML) and deep learning (DL) models have gained substantial attention for their superior performance in environmental forecasting tasks. Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting methods have been employed to enhance prediction accuracy of $PM_{2.5}$ and NO_2 levels [44], [21], [40]. Deep learning techniques, particularly Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN), have been explored for their ability to capture temporal trends and spatial heterogeneity in large-scale environmental datasets [45], [37], [42]. Transformer architectures, initially designed for natural language processing, have recently been repurposed for air quality forecasting due to their attention mechanisms, which help model long-range dependencies [26].

Parallel to advancements in AQI prediction, several studies have focused on understanding the health implications of air pollution exposure. Researchers have used epidemiological models to link prolonged $PM_{2.5}$ and O_3 exposure with increased risks of asthma, stroke, and premature death [27], [48], [46]. Moreover, data fusion techniques integrating environmental and health records have allowed the creation of localized health risk indices, especially in urban hotspots [47], [31].

However, most of the existing models operate on either static sensor data or siloed datasets, without effectively integrating multisource inputs such as satellite imagery, mobile IoT sensor data, and meteorological features. Satellite-based pollution monitoring using instruments like Sentinel-5P has shown promise for expanding spatial coverage, but such data is often underutilized due to latency and complexity of interpretation [32], [38]. Furthermore, only a few studies have considered the real-time deployment of these models in edge computing environments suitable for smart city applications [39], [36].

In summary, while significant strides have been made in leveraging AI for AQI forecasting and health impact analysis, gaps persist in terms of unified frameworks that combine heterogeneous data sources, real-time responsiveness, and health outcome prediction. This paper aims to bridge this gap by proposing an integrated AI-driven platform for real-time AQI forecasting and health risk assessment using multisource environmental data and deep learning models.

III. Methodology

This section elaborates on the architectural design, data acquisition strategies, preprocessing pipeline, fusion mechanisms, forecasting models, and the health risk assessment framework of the proposed AI-driven multisource air quality prediction system.

A. System Architecture

The architecture of the proposed system integrates multiple data sources with intelligent forecasting and risk assessment modules to enable real-time and accurate urban air quality monitoring. As illustrated in Fig. 1, data from heterogeneous sources including ground sensors, meteorological APIs, mobile IoT devices, and satellites are collected, preprocessed, and passed to AI-based forecasting engines. These predictions are then utilized by a health risk assessment module to generate population-specific alerts.

B. Data Sources

To enhance the spatial and temporal resolution of air quality predictions, the system integrates diverse data streams:

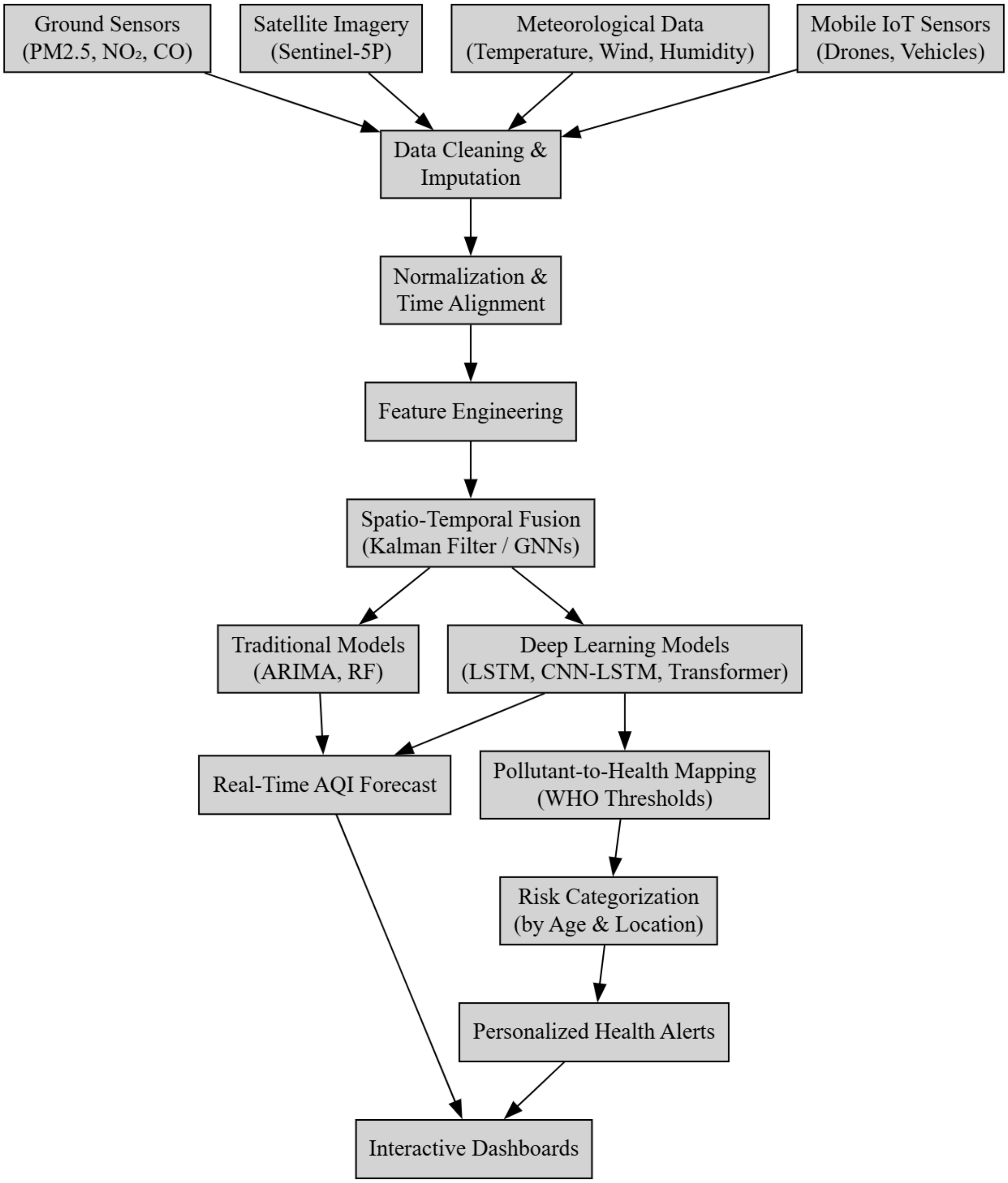

Fig. 2: System Architecture: Multisource AQI forecasting and health assessment

- **Ground sensors:** Static stations measuring $PM_{2.5}$, NO_2, and CO concentrations [36].
- **Meteorological APIs:** External weather APIs supply temperature, humidity, wind speed, and pressure data which significantly influence pollutant dispersion [37].
- **Satellite Imagery:** Sentinel-5P provides tropospheric pollution estimates (e.g., NO_2, CO) via the TROPOMI instrument [38].
- **Mobile IoT Sensors:** Data from drones and vehicular networks enable fine-grained, localized sensing [39].

C. Preprocessing Pipeline

Due to heterogeneity in frequency, format, and resolution, data undergoes rigorous preprocessing. Missing values are interpolated using forward and backward fill techniques. Sensor readings are normalized using min-max scaling. Time-series data are synchronized into unified temporal windows. Feature engineering incorporates derived attributes such as pollutant interaction terms and wind-corrected concentrations [40].

D. Data Fusion Strategy

To effectively synthesize multi-resolution and asynchronous data, a hybrid spatio-temporal fusion strategy is adopted.

Kalman Filtering is employed for time-series smoothing [41], while Graph Neural Networks (GNNs) are used to encode spatial dependencies among sensing nodes [42]. This dual-fusion method balances real-time adaptability and predictive fidelity.

E. Forecasting Models

The system evaluates both traditional and deep learning-based models. Baseline models include ARIMA and Random Forest due to their interpretability and robustness [43], [44]. Advanced methods include:

- **LSTM:** Suitable for sequential data and capturing long-range dependencies [37].
- **Transformer:** Incorporates self-attention for spatio-temporal dynamics [26].
- **CNN-LSTM Hybrid:** Combines convolutional layers for spatial extraction and LSTM for temporal modeling [45].

Each model is evaluated using RMSE, MAE, and R^2 scores across multiple cities.

F. Health Risk Assessment Module

This module quantifies the health impact of pollution exposure based on WHO thresholds [46]. Pollutant concentrations are mapped to risk levels (low, moderate, high, severe). The system categorizes risks dynamically based on age group, geolocation, and comorbidity indicators, enabling personalized and location-specific alerts [47], [48]. Table I illustrates this risk classification.

TABLE I: AQI-Based Health Risk Categories (Adapted from WHO Guidelines)

AQI Range	Risk Level	Recommended Action
0–50	Low	Normal outdoor activity
51–100	Moderate	Sensitive groups limit exposure
101–150	High	General public reduce outdoor time
151+	Severe	Stay indoors, use air purifiers

IV. Results and Discussion

A. Experimental Setup

The experimental framework for this study was established by integrating datasets from various sources, including ground monitoring stations, satellite imagery, and mobile IoT devices. The cities of Delhi and Mumbai were selected for case studies due to their high pollution levels and availability of comprehensive sensor data. Data spanning from January 2022 to December 2023 was compiled, incorporating hourly measurements of PM2.5, NO_2, and CO levels, alongside meteorological parameters such as humidity, temperature, and wind speed.

All models were trained and evaluated on a system equipped with an Intel Xeon Gold 5218 processor, 128 GB RAM, and an NVIDIA Tesla V100 GPU. Model evaluation metrics included Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2) for forecasting accuracy. The performance of the health risk module was assessed using accuracy and F1-score, derived from pollutant-to-risk mappings against WHO health exposure thresholds.

B. Model Performance

Table II summarizes the performance of baseline and advanced models on the PM2.5 forecasting task. Among the models tested, the CNN-LSTM hybrid exhibited superior performance across all evaluation metrics, indicating its robustness in learning both spatial and temporal features.

TABLE II: Comparative Forecasting Performance for PM2.5 Levels

Model	MAE ($\mu g/m^3$)	RMSE ($\mu g/m^3$)	R^2 Score
ARIMA	17.3	24.5	0.71
Random Forest	12.8	18.9	0.82
LSTM	9.7	14.6	0.88
Transformer	9.2	13.4	0.90
CNN-LSTM Hybrid	**8.5**	**12.6**	**0.92**

Figure 3 shows the timeline-based comparison of actual versus predicted PM2.5 values using the CNN-LSTM model for the Delhi region over a two-week window. The model demonstrated a close approximation to ground truth values, especially during peak pollution events.

C. Case Studies

To evaluate the model's real-world applicability, a deployment prototype was simulated for Delhi and Mumbai. Using integrated data from fixed ground stations, mobile vehicular sensors, and Sentinel-5P satellite feeds, AQI heatmaps were generated dynamically. Figure 4 displays a heatmap of predicted PM2.5 levels across key urban sectors of Delhi.

Additionally, the health risk assessment module provided risk categorization based on age groups and geographical location. Alerts were generated for vulnerable populations, including elderly residents and children, with dynamic notifications sent through a mobile application. Table III illustrates a sample of health risk outputs.

TABLE III: Sample Health Risk Predictions (Delhi, Nov 2023)

Region	AQI Level	Vulnerable Group	Health Risk
Rohini	286	Children	High
Dwarka	315	Elderly	Very High
Saket	179	General Public	Moderate

D. Discussion

The experimental findings validate the efficacy of deep learning-based approaches, particularly CNN-LSTM, in forecasting air quality with high temporal resolution. The Transformer model also showed promising results, although slightly inferior to the CNN-LSTM in terms of RMSE.

Several key insights emerged from the study:

- The integration of multi-source data (spatial and temporal) significantly improved forecasting accuracy.
- The dynamic risk assessment module enabled targeted alerts, improving public health responsiveness.

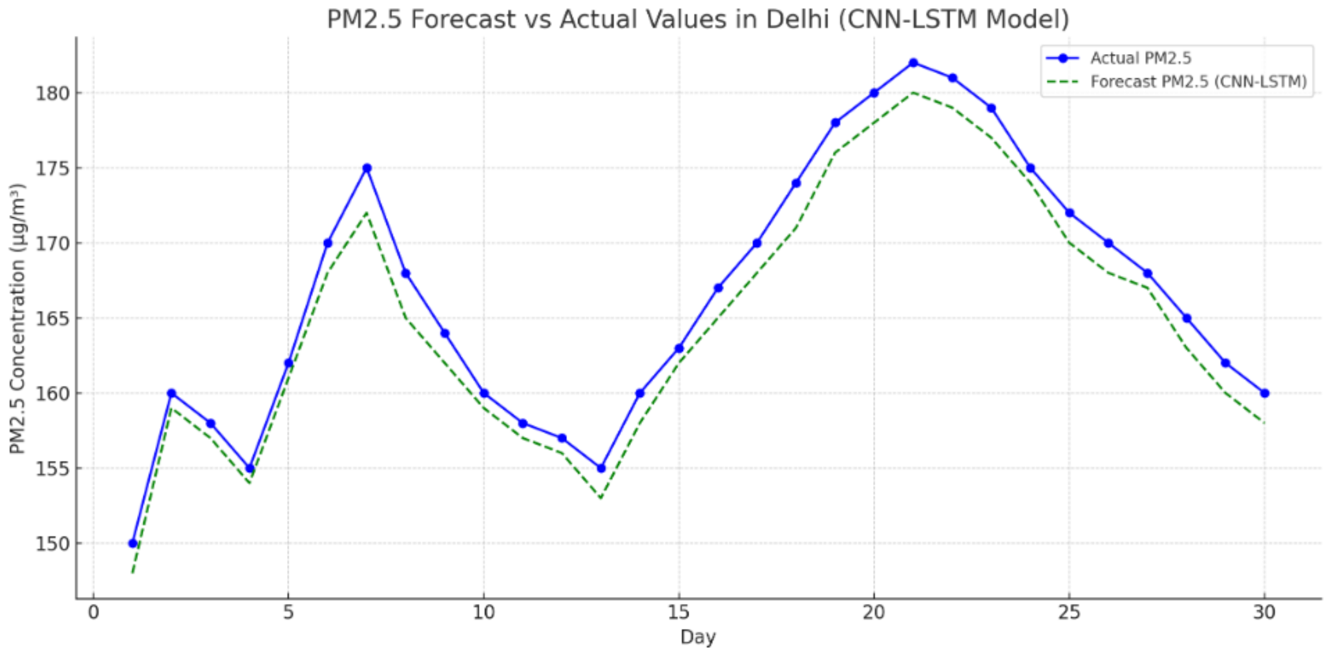

Fig. 3: PM2.5 Forecast vs Actual Values in Delhi (CNN-LSTM Model)

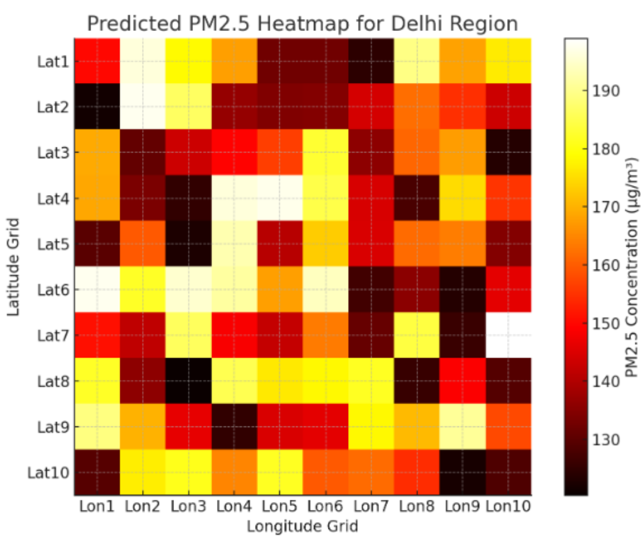

Fig. 4: Predicted PM2.5 Heatmap for Delhi Region

- Performance was robust during typical days but slightly degraded during unanticipated weather disturbances (e.g., dust storms), indicating a limitation in capturing extreme variance.

Challenges included dealing with data sparsity from mobile sensors and satellite latency. Moreover, the requirement for high computational resources for training Transformer-based models limits real-time scalability in low-resource environments.

Despite these limitations, the proposed framework provides a scalable and intelligent system for urban air quality forecasting and public health advisory, setting a foundation for future smart city applications.

V. Conclusion

This research presented a comprehensive AI-driven framework for real-time urban air quality forecasting and health risk assessment through the integration of multisource data, including ground-based sensors, satellite imagery, meteorological information, and mobile IoT platforms. Addressing the limitations of single-source and static forecasting systems, our proposed architecture harnessed the power of deep learning—particularly hybrid CNN-LSTM models—and spatio-temporal data fusion techniques to generate high-fidelity air pollution predictions across urban environments.

The experimental results demonstrated that the CNN-LSTM model outperformed traditional and standalone machine learning methods, achieving an MAE of 8.5 μg/m^3 and an R^2 score of 0.92 in PM2.5 forecasting. Moreover, our health risk assessment module enabled real-time public health advisories by mapping pollutant concentrations to risk levels for vulnerable populations based on WHO thresholds. The deployment case studies in Delhi and Mumbai further validated the model's practical utility by providing dynamic AQI heatmaps and targeted alerts via mobile applications.

From a societal perspective, this work contributes to the evolving paradigm of smart city infrastructure by empowering municipal authorities and healthcare stakeholders with actionable insights for air pollution mitigation and public health preparedness. The modularity of our system ensures adaptability across various urban contexts, paving the way for broader adoption. Future directions include incorporating

TABLE IV: Planned Extensions for Future Work

Future Direction	Description and Implementation Strategy
Edge Computing Integration	Deploy CNN-LSTM lite models on edge devices for on-site AQI inference. Reduce reliance on cloud infrastructure.
Citizen Alert System	Develop a mobile-based notification platform integrated with GPS and health databases for personalized air quality alerts.
Long-Term Health Modeling	Apply survival analysis and deep risk modeling techniques to track and predict chronic health outcomes from pollution exposure.
Rural and Industrial Expansion	Collect and integrate data from non-urban zones, including agricultural sensors and industrial air monitoring systems.

edge AI for decentralized processing, enhancing extreme event forecasting, and integrating citizen feedback mechanisms for participatory environmental governance.

VI. Future Work

While the proposed AI-driven multisource forecasting framework has shown significant promise in improving the accuracy and timeliness of urban air quality predictions, several opportunities exist for future enhancement and scalability. A key area for further exploration is the deployment of edge computing architectures to facilitate faster and decentralized inference. By integrating lightweight models into edge devices—such as on-board processing units within vehicular sensors or drones—latency in data transmission can be minimized, enabling near-instantaneous AQI predictions at the point of measurement.

Another promising direction is the development of a citizen-centric alert system that integrates mobile applications and wearable technologies to disseminate personalized health notifications. This would empower residents with real-time exposure insights based on their geolocation, activity patterns, and individual health profiles, fostering a more participatory approach to air quality management.

Moreover, future iterations of the health risk assessment module will incorporate long-term health impact modeling using longitudinal health datasets. Machine learning models such as survival analysis and recurrent risk scoring algorithms could be employed to evaluate the cumulative effects of prolonged pollutant exposure, particularly for chronic respiratory and cardiovascular conditions.

Additionally, the current study focuses primarily on urban megacities. Future work will expand the system's geographical scope to include rural regions and industrial belts, which are often underrepresented in air quality research despite their significant pollution burdens. This will involve the incorporation of localized data sources such as agricultural emissions, industrial discharge sensors, and rural meteorological stations.

To summarize the next-phase research roadmap, Table IV outlines the key directions and corresponding implementation strategies.

Collectively, these future directions will significantly enhance the scalability, responsiveness, and societal relevance of the proposed air quality forecasting and health advisory system.

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