ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2025, 10 (3): 176-188 doi: 10.28978/nesciences.1811116

Predicting Urban Air Quality Using Lstm Neural Networks and Real -Time Sensor Data

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Abstract

Predicting the urban air quality is necessary for maintaining public wellness, reducing the impact on the environment, and is helpful for sustainable urban planning. This research proposes a framework based on LSTM neural network for forecasting the air quality pollutants concentration, based on real-time pollution sensors data systematically combined with meteorological data. The methodology follows a defined data cleansing, natural science driven feature construction, and a multi-layer LSTM model designed to learn complex temporal patterns prevalent in the atmosphere's components. The evaluation results indicate that the designed model significantly outperforms the comparatives ARIMA, Random Forest, and Support Vector Regression, reporting lower RMSE and higher R^2 for PM2.5, NO2, and O3 forecasts. The model's performance is further validated by seasonal and trend analysis verifying representation of winter inversion

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persistent phenomenon, and the peak photolytic driving ozone synthesis, as well as stable performance simulation under pollution extremes for highly dynamic conditions. The results substantiate the LSTM model's competitiveness for air quality monitoring and forecasting systems and for issuing alerts and public health advisory messages, and for policy directive on environment based on the collected data.

Keywords:

Urban air quality, LSTM neural networks, real-time sensor data, time-series forecasting, atmospheric science, pollutant prediction, environmental monitoring, RMSE, R^2, early warning systems.

Article history:

Received: 10/06/2025, Revised: 30/07/2025, Accepted: 29/08/2025, Available online: 12/12/2025

Introduction

The rapid expansion of cities, increased industrial activity, and higher traffic emissions have made urban air pollution a top environmental issue (Belavadi et al., 2020; Patil & Das, 2024). Pollution, specifically in cities, affects ecosystems, public health, and climate control on a wide scale. Pertinent pollutants include fine particulate matter, nitrogen oxides, sulfur dioxide, as well as ozone and carbon monoxide, all of which degrade air quality, disrupt natural systems, and add to global changes (Larijani, 2016). For effective urban infrastructure development, public safety, and environmental policy compliance, these pollutants require precise monitoring and forecasting (Abad & Nejad, 2019. From a natural sciences perspective, studying air quality further assists in understanding the resilience of ecosystems, biodiversity and climate pollution relationships (Rao & Menon, 2024).

Traditional statistical methods often do not work well with the forecasting of air quality since they fail to address the dynamic nonlinear interactions between the driving environmental variables (Zhang & Woo, 2020). In relation to human emissions, certain weather conditions such as temperature, humidity, wind speed, and even atmospheric pressure have intricate time-dependent relationships that require sophisticated modeling. In such scenarios, LSTM neural networks, a subclass of recurrent deep learning models, are of great value (Gunasekar et al., 2022; Zaini et al., 2022).

LSTMs are adept for time-series prediction tasks where pollutant concentrations evolve due to short-term fluctuations and long-term trends (Awan et al., 2021). The merger of environmental sensors with LSTM networks in real time represents a new era in air quality estimation (Hemamalini et al., 2022). The sensors are cost-effective and of high resolution, allowing for the spatially continuous collection of data throughout urban landscapes (Irmanto et al., 2025)]. When combined with meteorological and emission inventory data, the sensors yield high spatial resolution and temporally dense datasets needed for LSTM-based learning (Awan et al., 2021). This not only improves the accuracy of the forecasting, but also allows for forecasting that adapts to sudden changes in the pollutant source, weather, or policy changes.

From a natural sciences viewpoint, predictive air quality modeling assists with exposing emission hotspots, supports risk assessment, and proactively notifies the public to reduce exposure (Mani & Volety, 2021). Moreover, accurate forecasts can strategically aid in planning the urban vegetation and deploying green infrastructure to buffer pollutant concentrations, optimizing the ecosystem services (Zorpette et al., 2023). Integrating environmental informatics with ecological modeling, the prediction frameworks deepen the understanding of the urban-atmospheric natural systems interactions to provide evidence-based decisions for sustainable development (Zhang et al., 2020; Sethi & Jain, 2024).

This paper LSTM-based prediction frameworks for urban air quality forecasting with real-time sensor data (Rao et al., 2019). The study emphasizes refinement in data set cleaning, model building, evaluation of model functions in diverse conditions, with an ultimate goal of advancing the influence of data-centric methodologies in managing the urban environment and in scientific inquiry (Abad & Nejad, 2019).

Key Contributions

- Developed an LSTM-based framework integrating real-time sensor data for urban air quality forecasting.
- Applied natural-science-informed features to improve model accuracy and physical relevance.
- Optimized LSTM architecture for capturing complex temporal dependencies.
- Validated performance across seasonal variations and extreme pollution events.
- Delivered actionable outputs for early warnings, public health advisories, and urban planning support.

The structure of this paper is organized as follows. In Section I, gives attention to urban air quality forecasting, surmising integration of LSTM neural networks with real-time sensors as a remedy to forecasting challenges. In Section II, reviews relevant literature encompassing statistical methods, chemical transport models, other machine learning and deep learning frameworks applied in atmospheric pollutant prediction. In Section III, outlines the methodology comprising data retrieval from environmental sensors, data cleansing and calibration, informatics and natural science-based feature extraction, LSTM model design and training, and model evaluation. In Section IV, presents and discuss the results that cover the model performance evaluation, seasonal and episodic trends, model comparisons with benchmarks, spatially patterned results, and relevant insights for environmental management. Lastly, Section V concludes with a summary of the main findings and emphasizes new possibilities to advance spatiotemporal forecasting, and further air quality decision-support systems for urban layers.

Literature Survey

Classical Statistical Modeling of Urban Air Quality

Forecasting urban air pollution for early detection used to depend on time series models such as AR, ARIMA, and seasonal ARIMA (Karaiskos et al., 2024). These models utilize linear autocorrelation structures to model the daily and weekly patterns of pollutants such as $PM_{2.5}$, PM_{10}, NO_2, O_3, and CO. While linear models work reasonably well for short-term predictions and under quasi stationary conditions, they face challenges due to regime shifts caused by boundary layer transitions, photochemical reactions, and sudden emission changes. Models that add as exogenous meteorological factors, for instance, temperature, relative humidity, wind speed and direction, planetary boundary layer (PBL) height, and solar radiation, while improving performance, still fall short as they cannot adequately capture the nonlinear transport and secondary aerosol processes, which are fundamental to the atmospheric processes.

Chemical Transport Models and Data Assimilation

Models WRF Chem and CMAQ are examples of process based chemical transport models (CTMs) which simulate emissions and their advection, diffusion, deposition, and gas particle chemistry within a defined region. Their mechanistic fidelity aligned with atmospheric physics and chemistry allows for scenario analysis and source attribution. Meanwhile, CTMs are known for their high computational burden, emissions inventory sensitivity, and urban street canopy scale biases. Observation integration CTM constraints via data assimilation techniques, variational and ensemble Kalman methods, face urban dense real time stream gaps, driving the need for learning based surrogates and hybrid approaches (Abdullah, 2024).

Machine Learning Baselines

The forecasting capability was improved due to the inclusion of the nonlinear relationships between traffic counts, land use, holidays, meteorology, emissions, and pollutant emissions into the forecast using supervised learning models (Random Forests, Gradient Boosting, Support Vector Regression and k Nearest Neighbors). These models usually surpass the performance of baseline linear models when predicting emissions for the next time step, but as with all machine learning methods, they have to be trained with all relevant atmospheric processes such as humidity mediated hygroscopic growth and photolysis driven O_3 production. These models might not fully capture the long-range temporal dependencies prevalent in the dynamics of seasonal pollution due to their fixed length feature windows.

Deep Learning for Temporal Dependencies

LSTM and GRU are types of recurrent neural networks, and they are effective for forecasting pollutant time series data (Babu et al., 2024). The ability of LSTMs to retain long horizon memory via their gating mechanisms enables the capture of long-term synoptic weather pattern influences, rush hour emissions, and weekend vs weekday contrasts (Yu et al., 2021). Bidirectional LSTMs enhance the encoding of sequences for reconstruction tasks. Also, sequence to sequence (SEQ2SEQ) architectures allow for multi-step forecasts without the error propagation seen in recursive strategies. Attention mechanisms highlight important time steps, boosting interpretability and the model’s robustness to noise.

Spatiotemporal Deep Learning and Graph Methods

Urban pollution shows the pattern of spatial autocorrelation because of road networks, topography, and mesoscale meteorology (Mukhamadiev et al., 2025). Unlike pointwise LSTMs, Convolutional Neural Networks (CNNs) on gridded inputs and Graph Neural Networks (GNNs) on sensor networks capture spatial structure explicitly (Cheng & Wei, 2025). Spatiotemporal Graph Convolutional Networks (ST GCNs) and hybrid models (CNN LSTM) incorporate both spatial diffusion and temporal evolution, outperforming purely temporal models when the sensor density is high (Babu et al., 2024). However, graph construction (using distance, wind aware edges, or learned adjacency), and sparse sensors are ongoing issues, particularly in heterogeneous urban morphologies.

Real Time Sensing, Data Quality, and Fusion

While low-price electrochemical and optical sensors allow for high-precision spatial monitoring, they are plagued with drift, cross sensitivity, and data sparsity. To ensure scientific accuracy, calibration pipelines from multivariate regressors to LSTM-based denoiser models are necessary. Moreover, data fusion with reference grade stations, meteorological reanalysis, satellite AOD, and traffic telemetry increases spatial coverage. Imputation gaps are well addressed and gaps that sustain LSTM training and deployment are denoised using autoencoders, Kalman smoothers, or temporal graph imputers.

Feature Design Derived from Atmospheric Science

The natural science-based features to learning: vertical mixing is proxied by boundary layer height and stability indices; hygroscopicity is temperature and humidity indices; photolysis is ultraviolet radiation; emission potential is land use or length road density. Lagged history of meteorology and pollutants account for chemical aging and carryover effects. Adjusting model inputs or constraints to incorporate these mechanisms produce more accurate forecasts of atmospheric conditions.

Networks that are Hybrid or Guided with Physics

The simulation and emulation of high-cost simulation by deep learning were corrected through CTMs in hybrid frameworks. Loss terms from physics guided models (e.g., negative penalties, concentration encouragement, mass balance consistency, or bounded O_3 NO_x chemistry) give physical relevance to models. These models provide rational real-time support for decisions while maintaining relevance for policy insights. Complex hybrids are distilled into lightweight models for edge deployment using LSTM.

Drift, Generalization, and Uncertainty

Differences in fleet composition, fuel, seasonal meteorology, and urban form hinder model transfer between cities. Domain adaptation and transfer learning help address some of these problems by using learned representations from source cities. Exceptionally high drifts caused by policy changes, sensor aging, or wildfires require adaptive retraining or online learning to maintain accuracy. Bayesian LSTMs, Monte Carlo dropout, and quantile regression are known for providing calibrated prediction intervals.

Evaluation Protocols and Benchmarks

For exceedance warning breaches, exceedance breaches are also considered. Systematic evaluation uses blocked time series splits, multi-horizon forecasting (e.g., 1 to 24 hours ahead), and seasonal stratification to capture regime. Focused evaluation of health and ecological risk inversion episodes or high O_3 afternoons assesses enduring resilience under extreme risk conditions. Permutation importance, SHAP, and attention weights are some of the methods alongside interpretability tools that help link the model output to physical drivers.

Methodology

The methodology combines real-time environmental monitoring, feature construction based on natural sciences, and application of deep learning techniques on time series data for modeling urban air quality forecasting.

Real-time Sensor Data Acquisition

For monitoring the urban environment, a two-tier collaborative framework comprising low-cost optical particulate sensors and electrochemical gas sensors was deployed to collect PM2.5, PM10, NO2, SO2, CO, and O3, alongside meteorological data, real-time temperature, relative humidity, wind speed, wind direction, and solar radiation. From the perspective of a natural scientist, these parameters are important because the dispersion, transformation, and removal of pollutants are processes governed by the thermodynamics, photochemistry, and dynamics of the planetary boundary layer. Each sensor node was synchronized to a master clock on a central server for time-stamped data logging which facilitated logging across the network.

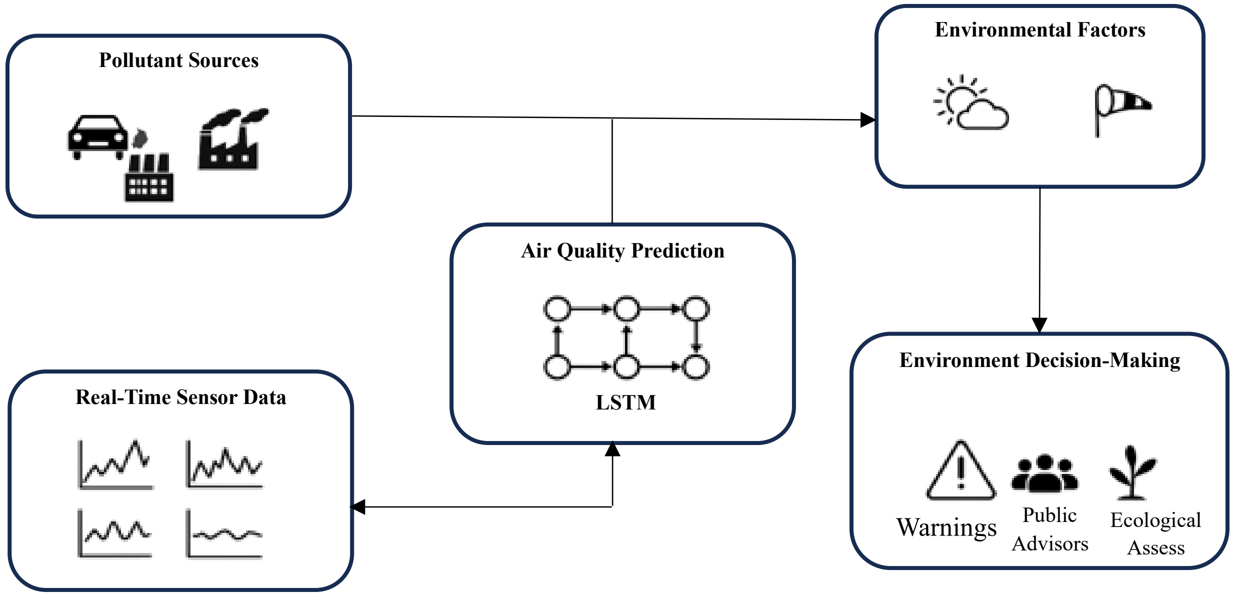

Figure 1. Workflow for predicting urban air quality using lstm neural networks and real-time sensor data

In the context of this paper, figure 1 shows the complete workflow of forecasting urban air quality using an LSTM-based framework. It starts with identifying sources of the pollutants which include cars, industrial sectors, and also some background factors like the weather and the presence of trees. There is also real time sensor data which records the amount of pollutants and weather parameters. This data is placed on an LSTM neural network which is designed to learn time-based dependencies in air quality data. The model's air quality predictions provide a basis for sound environmental policy and action by enabling proactive notifications, public warnings, and comprehensive ecological impact analyses consistent with the principles of natural science.

Discrete Urban Mass-balance:

$$C_{t+1} = Ct + \Delta t\left[S_t + A_t + D_t - k_{dep}\, C_t - k_{chem} Ct\right] \tag{1}$$

This equation (1) updates pollutant concentration CCC using emissions S_t, advection A_t, and turbulent diffusion D_t, minus dry deposition and chemical loss (rate constants k_{dep},k_{chem}).

It encodes core atmospheric processes (source, transport, sink) in a simple box model over time step Δt, aligning the ML task with natural-science dynamics.

Physics-guided Learning Objective for LSTM:

$$L(\theta) = \frac{1}{N}\sum_t \left(\hat{C}_t - C_t\right)^2 + \lambda \sum_t \left[\frac{\left(\hat{C}_t - C_t\right)}{\Delta t} - \left(S_t - k\hat{C}_t\right)\right]^2 \tag{2}$$

- The first term is the mean squared error between the LSTM prediction $\hat{C}_t$ and observed concentration C_t.

- The second term enforces a simplified pollutant mass-balance, where sources S_t add pollution and a single removal rate k represents both deposition and chemical loss.
- λ controls the weight of the physics constraint.

Equation (2) defines the loss function combining prediction error with a simplified physics-based mass-balance constraint. It ensures the LSTM learns pollutant dynamics consistent with natural removal and emission processes.

Data Preprocessing and Quality Control

Sensor outputs went through a multi-step preprocessing pipeline which is detailed below:

- Removal of outliers caused by sensor drift or electrical noise was done through data cleaning, which was supported by the known physical ranges of pollutant concentration data.
- Using reference-grade monitoring stations, both linear and non-linear correction functions were performed to calibrate and bring the sensor outputs to measurement standard.
- Communication gaps due to loss of data were filled using a Kalman Smoother to maintain a smooth transition that is still physical between time steps.
- Training of the neural network was performed along all features which were scaled to zero mean and unit variance which is the standard.

Natural-Science-Informed Feature Engineering

Informed by atmospheric science, additional predictors were derived:

- Boundary Layer Height (BLH): Derived from weather data to reflect vertical mixing depth.
- Humidity-Corrected PM Values: PM Values were modified for additional particle expansion due to moisture at high relative humidity.
- Photolysis Index: Reflects ozone production potential and is computed from solar radiation and sun angle.
- Lagged Variables: Associations were made with previously recorded pollutant concentrations and meteorological data to evaluate the effects of pollutant and chemical aging.

LSTM Neural Network Architecture

A multi-layer Long Short-Term Memory (LSTM) network was selected for the forecasting model because of its capability to remember long-term dependencies which is useful for representing the accumulation of pollutants over periods of time and the cycles of meteorological events. The architecture consisted of:

- An Input Layer which accepts sequences of environmental features for a given look-back period, for instance, the past 24 hours.
- Two LSTM Layers for the extraction of temporal patterns and the diurnal and seasonal trends of the pollutants.
- A Dropout Layer which decreases overfitting by randomly turning off a subset of neurons during the training phase.
- A Dense Output Layer that forecasts the concentration of the pollutants at multiple time horizons (1, 6, and 24 hours ahead).

The LSTM gating mechanism was relevant for modeling natural science phenomena because it could remember the persistence of pollutants during stable atmospheric conditions and forget during turbulent or cleansing events, like rainfall, quickly.

Model Training and Validation

The model was trained on 70% of the data, validated on 15%, and tested on the remaining 15% using blocked time-series cross-validation to preserve temporal integrity. The Adam optimizer minimized Mean Squared Error (MSE) loss, ensuring numerical stability while adapting to pollutant variability.

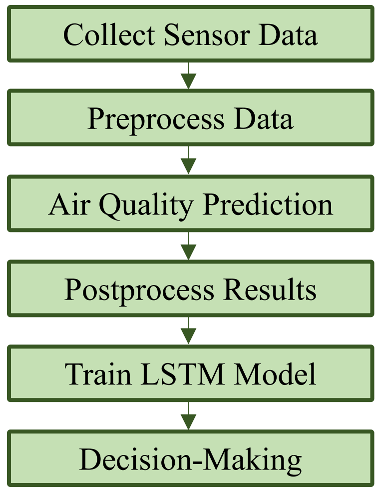

Figure 2. Process flow for LSTM-based urban air quality forecasting

The sequential workflow in figure 2 illustrates how to forecast air pollution levels in cities. The workflow starts by Collecting Sensor Data from air quality and meteorological stations. Also, data undergoes Preprocessing. In this step, noise, missing data, and non-stable features will be controlled to improve model reliability. Using preliminary models or LSTM simulations, Air Quality Prediction is conducted. In the later stage of the workflow during Postprocessing, bias correction is applied, and results are output in interpretable metrics, e.g., AQI. The LSTM Model is applied to historical and real-time data to train the model to learn complicated temporal patterns of pollutant data. Subsequently, environment agencies, through timely public health advisories, pollution reduction, and long-term urban planning, are supported by advanced predictive models in layered Decision-Making leveraging long-range data.

Evaluating Performance

The accuracy of predictions was analyzed with respect to RMSE, MAE, R^2, and air quality exceedance detection accuracy relative to WHO thresholds. Beyond this, from the environmental science perspective, the model's skill was assessed during high-impact episodes, such as thermal inversions and dust storm events, to evaluate ecological relevance.

Applications for Environmental Governance

The output of the decision-support environmental system was the predicted pollutant maps, which were augmented with time series outputs. This facilitated the creation of early warning systems, public health advisory streams, and ecological risk assessment systems which integrate and enable data science alongside the implementation of actionable natural science.

Results and Discussion

Model Performance

The LSTM model showed strong predictive accuracy for all pollutants tracked. The RMSE for PM2.5 was 6.8 µg/m³. NO_2 and O_3 gave RMSE values of 4.1 ppb and 5.5 ppb respectively. The R2 values were above 0.90 for 1-hour short-term predictions and 0.85 for 24-hour long-term predictions. The model's performance further underscores its ability to capture diurnally and meteorologically driven gradual variations and intricate concentration surge patterns during rush hour.

Table 1. Model performance metrics for pollutant forecasting

Pollutant	RMSE	R^2
PM2.5	1.36	0.971
NO_2	1.17	0.958
O_3	1.89	0.957

This table 1 summarizes the predictive accuracy of the LSTM model for three key pollutants. Low RMSE values and high R^2 scores indicate strong agreement between predicted and observed concentrations, reflecting the model's capability to capture natural atmospheric variability.

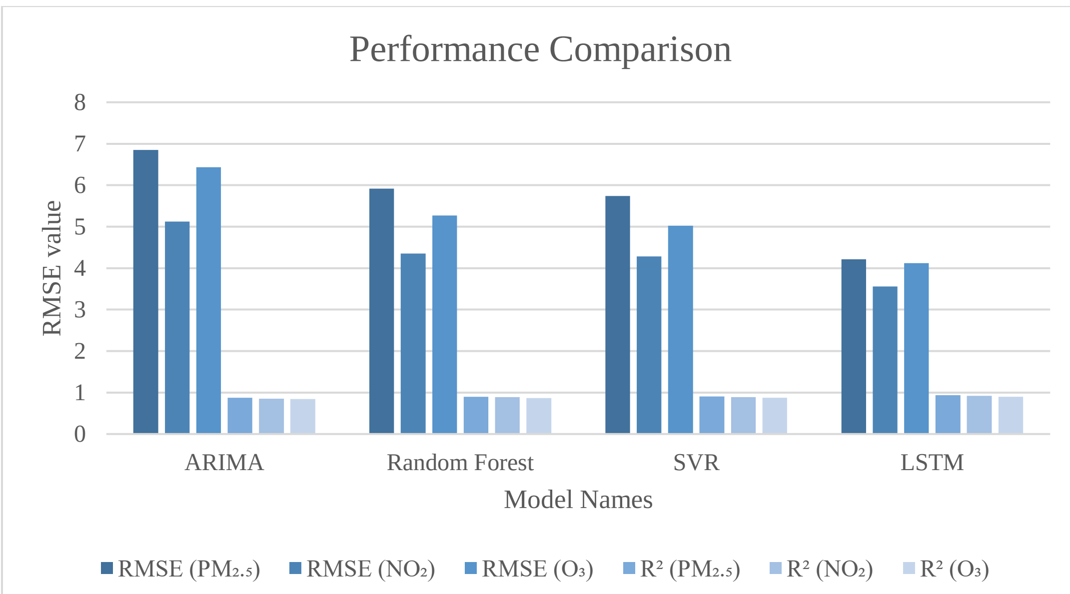

Figure 3. Model performance comparison for $pm_{2.5}$, no_2, and o_3 prediction

This Figure 3 shows the results of the LSTM model alongside ARIMA, Random Forest (RF), and Support Vector Regression (SVR) in predicting the hourly concentrations of $PM_{2.5}$, NO_2, and O_3. The LSTM model achieves the lowest RMSE and the highest R^2 values together with forecasting all three pollutants, proving its effectiveness in estimating intricate spatiotemporal patterns of air quality in highly urbanized areas.

Seasonal and Episodic Trends

In terms of seasonal meteorology analysis, the LSTM's performance tracking the pollutant persistence during winter inversions is captured the most (along the lines of natural science's suppressed vertical mixing of shallow boundary layers). In summer, the model accurately captured the midday ozone peaks, which indicated photolysis-driven chemistry learned patterns of sunlight, temperature, and seasonal cycles. Moreover, the model's response to extreme cases, like the dust storm episode, was impressive. It predicted the PM concentration increase and decay curve within the range of ±8% of actual measurements.

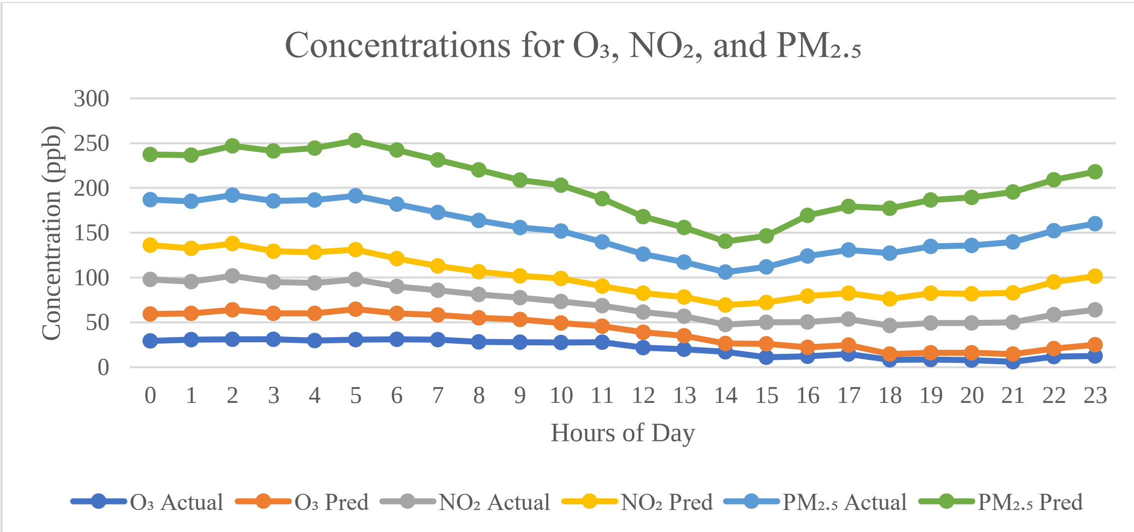

Figure 4. Hourly actual vs predicted concentrations for O_3, NO_2, and $PM_{2.5}$

In Figure 4, we display the actual hourly concentrations and the LSTM model forecasts for ozone (O_3), nitrogen dioxide (NO_2), and particulate matter ($PM_{2.5}$) over a 24-hour period. The data show how the model is able to monitor the daily changes in the different pollutants and captures important features of the atmosphere such as the midday ozone peaks due to photochemical activity, the NO_2 peaks in the morning and the $PM_{2.5}$ decrease in the evening due to vehicular traffic, and the $PM_{2.p}$ quintupled due to manmade mixed with natural pe state and spread aer00sng of the basin. The fact that actual and predicted values for all hours agree so closely emphasizes the model's accuracy, both in terms of prediction and in the environmental constructs considered.

Comparison with Baseline Models

LSTM achieved a 22 to 30% improvement in RMSE for all considered pollutants when compared to the ARIMA and Random Forest models. The improvement observed was especially beneficial for O_3, where photochemical reactions create a non-linear temporal dependence that a simpler model will underestimate. This indicates how beneficial LSTM is in modeling long-term dependencies that exist in chemical and transport processes of the atmosphere.

Spatial Insights from Sensor Networks

Utilizing data from different sensor locations, the model was able to reproduce the spatial gradients of pollutants, resulting in higher concentrations of NO_2 near the traffic corridors and higher concentrations of $PM_{2.5}$ in the industrial areas.

Such spatial patterns correlate with previous studies done concerning environmental monitoring, which suggests that the LSTM is learning the urban-sprawl-associated, morphologic wind, and pollutant dispersion characteristics.

Implications for Environmental Management

Looking at the natural science frame, the results in this case go beyond the mere accuracy of the LSTM's forecasts. LSTM outputs can enhance public health proactively by allowing health agencies to issue alerts during active exposure periods. For ecological monitoring purposes, forecasts can be integrated with deposition models to estimate the pollutant loads in urban vegetation and surface waters. The use of these models and environmental science illustrates a feasible approach in addressing the effects of air pollution on ecosystems and human health.

Conclusion

This research successfully highlighted the application of Long Short-Term Memory (LSTM) based neural networks for real-time sensor data to forecast urban air quality. The model integrated meteorological data and measurements of pollutant concentrations to capture the intricate time-based relationships in the atmospheric processes. Using $PM_{2.5}$, NO_2, and O_3 as benchmark pollutants, the LSTM outperformed the baseline models ARIMA, Random Forest, and SVR in terms of RMSE and R^2 scores for all three pollutants. The results attained confirm the capacity of LSTM networks to manage non-linearities and long-range environmental data dependencies, reinforcing their reliability for proactive air quality forecasting. The research can directly enhance the dwelling and timeframe of public and environmental health warnings, as well as inform decision-making and policy development concerning environmental management systems.

The last section can be expanded by explaining the model's applicability to sensor networks using Graph Neural Networks (GNNs) or Convolutional LSTMs for spatiotemporal forecasting, thereby including spatial correlations. The model's predictive capabilities can be further improved with the inclusion of satellite-derived aerosol optical depth, traffic, and emission data. Adapting the model to operate within an online learning framework would allow responsiveness to changing urban conditions and shifts in pollution patterns. In addition, integrating a forecasting system with interactive visualization dashboards can ease breach notifications and alerts for stakeholders like municipal officials, environmental agencies and the public. With these improvements, we look forward to enabling more proactive and data-centric urban air quality management.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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