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Real-Time Air Quality Prediction Using IoT-Integrated Polymer Sensors and Recurrent Neural Networks

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Abstract

Real-time air quality monitoring remains a critical challenge in urban environments, where traditional sensor infrastructures often suffer from limited responsiveness, poor scalability, and high deployment costs. The increasing prevalence of NO_2 pollution, a key contributor to respiratory and cardiovascular ailments, demands advanced sensing platforms capable of both accurate detection and predictive inference. Existing methods either rely on rigid electronic sensors lacking adaptability or on statistical forecasting models that fail to capture nonlinear and temporal dynamics inherent in gas dispersion patterns. Moreover, few efforts effectively integrate polymer-based sensing materials with real-time intelligent inference pipelines. To address this, we propose an IoT-integrated system leveraging polymer-composite gas sensors in conjunction with a Long Short-Term Memory (LSTM) neural architecture for dynamic NO_2 prediction. The polymer matrix, synthesized with conductive fillers and tailored for gas sensitivity, provides enhanced selectivity and faster response rates. These sensors are embedded within a low-latency wireless acquisition framework, enabling real-time data streaming to a cloud-based LSTM engine for time-series prediction. Experimental results demonstrate that the proposed model outperforms conventional baselines including ARIMA, SVR, and Random Forest in terms of prediction accuracy (MAE: 2.14 ppb, R^2: 0.93), while maintaining sub-second latency in edge-to-cloud inference cycles. Sensitivity analysis confirms superior sensor response across varying NO_2 concentrations under controlled and outdoor conditions. This fusion of polymer-based sensing and deep sequence learning presents a scalable and adaptive architecture for smart environmental monitoring. The approach holds potential for deployment in edge-intelligent air quality systems, supporting public health policy and sustainable urban planning.

Keywords: Polymer-composite sensors, air quality prediction, IOT monitoring, LSTM neural networks, real-time environmental sensing

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INTRODUCTION

Air pollution is still one of the biggest problems that urban populations face around the world, which has an overall effect on both the environment and public health. The unique difficulty with monitoring and predicting air quality is a result of the instinctive nature of pollutant dispersal, which is dependent on many factors such as weather conditions, human activity, and location. Traditional air quality measuring techniques are effective in some contexts but are bound by fixed sensor stations that restrict cost and range of infrastructure. Thus, we must create more low-cost, flexible, and real-time air quality monitoring systems so that the fight against the international call for environmental sustainability and public health security in urban cities [1], [2] can be made easy. The recent advancement in Internet of Things (IoT) technologies has resulted in the deployment of sensor networks that will enable the monitoring of the environment. The use of a polymer sensor for IoT monitoring is promising because it is flexible per se, cost-effective with sensitivity to many air pollutants like PM2.5, CO_2, NO_2, and VOCs [3], [4]. The sensors may also have some advantages over traditional sensor technologies, such as lower power usage and flexibility and a desirable requirement for real-time air quality monitoring networks [5], [6]. Recently, machine learning (ML) models, i.e., recurrent neural networks (RNNs), have shown enormous potential to enhance air quality prediction. RNNs the Long Short-Term Memory (LSTM) Networks, in particular, are particularly suitable for time-series prediction predictions since they possess the ability to identify long-term dependencies within sequence data [7], [8]. By utilizing these models with historical air quality data, the ability to predict future pollutant levels can be achieved with a high-level of accuracy to enable proactive responses to minimize negative environmental impacts. The convergence of IoT sensors with deep learning models has become the focus of many researchers looking to create smart air quality monitoring [9], [10]. While the advancement of machine learning and IoT technologies has made strides in the environmental monitoring space, few of the current studies have investigated the couple of polymer-sensing-based sensors with deep learning models to predict real-time future air quality. Although some studies have explored the use of a combination of traditional sensors and various machine learning techniques, there is a research gap around polymer composite based sensors integrated with more advanced future prediction techniques, including recurrent neural networks (RNNs) such as LSTMs. Hence, this research aims to bridge this gap by proposing a new system which combines IoT integrated polymer-based sensors on-ground, with RNN future air quality prediction models, which presents a more scalable and timely approach to urban air pollution management [11], [12]. Recent studies have also pointed to how flexible low-cost polymer based sensors can contribute to more scalable and accessible environmental monitoring systems. Sundararajan et al. (2025) and Begum et al. (2024) have explored the considerable potential of polymer sensors in combination with machine learning methods, particularly real-time prediction of air quality and anomaly detection [13], [14]. Moreover, J. R. R et al. (2025), outlined how due to the IoT networks providing digital twins of urban air quality prediction, the combination of IoT networks with polymer sensor technology could improve air quality prediction efficiency [15].

The central contribution of this research is a framework that will aid in the predictive analytics of air quality parameters in real-time because of a joint framework of IoT polymer sensors that detect pollutants and deep learning LSTM models to predict air quality parameters accurately. The system will provide not only a mechanism for real-time prediction of air quality parameters but will be a cost-effective approach to deploying the system in large urban areas, which has the potential to be of great value for smart cities and sustainable urban development. This project combined the use of flexible polymer sensors with predictive machine learning approaches, to transform the current issues faced in environmental monitoring and management.

LITERATURE REVIEW

The evolution from centralized sensor clusters to distributed and real-time systems is intrinsically intertwined with edge and fog computing frameworks. In one case study, a fog-enabled system's design processed pollutant concentrations "at the edge" of the network and the fog framework was not only able to reduce latency, it was evidenced that the fog-based predictive service could provide more agile predictions for smart-city applications [16]. Hybrid IoT architecture that integrated mobile and fixed nodes reached localized air quality forecasting and better spatial resolution [17] and the mobile -fixed fusion architecture example was used to track pollutant plumes within users proximity. Although traditional ML based classifiers were deployed in municipal air pollution contexts, deep learning based air pollution models from the same architecture with a Dynamic Learning Multi-Layer Neural Network classifiers experienced accuracy improvements in varying environments [18-19]. Fuzzy logic and deep learning have also been employed in combination to address data uncertainties and non-linearities. One IoT-aware model that incorporated conditional random fields with bi-directional LSTM architectural layers was able to accurately detect pollution anomalies in urban corridors [20]; while pure deep learning paths that used stacked LSTM and GRU networks significantly improved long-range PM2.5 forecasting capabilities by detecting multi-scale temporal dependencies [21]. To further address spatial interdependencies in air pollution research, spatio-temporal graph convolutional networks were used to detect pollutant diffusion across sensor grids, where the values of the predicted outcomes were superiorly accurate than pointwise models [22]. Multivariate LSTM ensembles, with embedded meteorological covariates, as well, has improved on univariate approaches, as shown in benchmark comparisons [23], and there was evidence from time-series experiments that pure LSTM networks outperformed as models of trends of Air Quality Index [24]. Hybrid deep learning frameworks including CNN as feature extractor and LSTM as sequence learner improved forecast accuracy even more by utilizing frequency and time domain representations [25]. There has also been interest in hybrid time-frequency domain models which have also included deep architectures. Hybrid models that have transformed time-series signals into spectrogram representations and then feed them as input to convolutional and recurrent layers improved detection of pollutant peaks and reduced false alarms [26-27]. In parallel, developments such as reservoir computing have also given researchers opportunities to lightweight online trajectory prediction of constrained resource IoT devices with echo state networks used for environmental sensing tasks [29]. In addition transfer-learning with the original applications of firmware classification is now being utilized to re-calibrate models of air quality‹ so that different sensor types can be fine-tuned and, such an approach does not require extensive training [28]. Similarly, Autoformer architectures that analyse time series data via decomposition and attention mechanisms have also been repurposed to forecasting pollutants via its solid handling of long-term trend management [32]. In addition, survey studies underscore the critical importance of AI–big data analytics in building automation systems and organizations' ability to implement scalable models in cyber-physical infrastructures [30]. Graph-based methods and federated learning are emerging methods for air quality intelligence. High-resolution forecasting systems that combine source apportionment with graph neural networks were capable of delivering pollutant sources at a more refined resolution for urban centres across Europe [33]. By sufficiently optimizing message passing algorithms, real-time GNNs from cloth simulation, have been adopted in environment models which suggests domain potential for fast inference [34]. Federated learning frameworks that secure data privacy over distributed sensors, are beginning to show potential in continuous air quality monitoring as they allow model updates between sensors across collaborative environments, whilst the raw data is never exchanged [35]. While wildfire-impact forecasting [9] and peak-bias correction algorithms [10] are among several advancements, the vast majority of applications still rely on fixed electrochemical transducers while polymer nanocomposite vectors remain largely unexplored. Both readiness assessments for urban digital twins [6] and spatio-temporal GIS alerting systems [36-37] utilize fixed sensor modules or simple rule-based schemes and ignore conformal high sensitivity polymer arrays that capture heterogeneous pollutant distributions. Even the road-type pollutant profiling using AutoML pipelines [38-39] leverages standard MEMS devices and fails to take advantage of chemiresistor improvements provided by polymer-composite films. In total, Table 1 highlights a material-model integration void gaps which we address by integrating the polymer-composite sensor nodes into our LSTM driven, real-time air-quality forecasting forecasting systems.

METHODOLOGY

This section details the design, fabrication, and integration of the proposed polymer-composite sensor network with an LSTM-based prediction framework. At the heart of our approach is a seamless polymer–model integration. Conformal chemiresistor films—made from polyaniline reinforced with carbon nanotubes—sense $PM_{2.5}$ and NO_2 fluctuations as raw resistance changes, which are streamed directly into an LSTM prediction engine. This unified material-to-algorithm pipeline removes the need for separate calibration and signal-processing steps, delivering pollutant forecasts in under one second with heightened sensitivity and accuracy. The outcome is a lightweight, scalable IoT framework that truly operates in real time.

Polymer-Composite Sensor Design and Fabrication

The core sensing element consists of a flexible chemiresistor film formed by dispersing multi-walled carbon nanotubes (MWCNTs) within a polyaniline (PANI) matrix at an optimized mass ratio of 5:1. After dissolving the constituents in N-methyl-2-pyrrolidone, the mixture underwent prolonged ultrasonication to achieve uniform nanotube exfoliation and polymer chain alignment. Subsequently, the homogenous suspension was drop-cast onto interdigitated gold electrodes patterned on a 50-µm-thick polyimide substrate. To consolidate the film and remove residual solvent, the sensor array was annealed at 80 °C under vacuum for two hours, resulting in a crack-free, adherent layer with consistent thickness. Table 2 presents the detailed composition, baseline resistance (R_0), sensitivity ($\Delta R/R_0$ per ppm), and response time (t_{90}) for each target analytic, while Figure 1 illustrates the multilayer stack-up—including the polymer composite, electrode geometry, and protective encapsulation.

Table 1. Key Research Gaps in Recent IoT–ML Air-Quality Studies.

S. No.	Author(s) / Year [Ref]	Title / Focus & Methodology / Key Findings	Limitations / Gaps Identified	Proposed Polymer-Model Fusion
1	Huang et al. (2025) [9]	Next-Gen AQ Prediction in Unified Forecast System: wildfire emission modeling + deep-learning for $PM_{2.5}$ forecasts; improved predictability of wildfire impacts.	Relies on high-grade fixed sensors; omits polymer-composite sensor materials for distributed, low-cost networks.	Embed low-cost polymer-composite sensor nodes into the unified forecasting pipeline, providing spatially dense $PM_{2.5}$ data for LSTM models.
2	Frischmon et al. (2025) [10]	Peak Concentration Quantification via Data Weighting: weighted sampling corrects peak bias; enhances $PM_{2.5}$ peak estimation accuracy.	Focuses on algorithmic correction; no innovation in sensor materials—polymer composites that could naturally improve peak response are unaddressed.	Integrate polymer-composite chemiresistors with intrinsic high-peak sensitivity, reducing reliance on weighting and enhancing real-time peak detection.
3	Cowell et al. (2025) [6]	Real-Time Interventions with Low-Cost IoT Networks: evaluation of sensor readiness for urban digital-twin applications; near-real-time support shown.	Assessment based on electrochemical sensors; lacks exploration of polymer sensors for improved sensitivity and form-factor flexibility.	Deploy conformal polymer-composite sensor films within digital-twin architectures, boosting data fidelity and enabling seamless integration on varied surfaces.
4	Kirana et al. (2025) [36]	Web-GIS Spatio-Temporal AQ Monitoring: decision-tree alerts on historical data; effective spatial visualization for public alerts.	Uses rule-based ML; does not incorporate deep-learning nor polymer sensor materials, limiting predictive accuracy and sensor innovation.	Replace static models with LSTM-driven forecasting fed by polymer-composite sensor networks, enhancing temporal prediction and sensor durability in Web-GIS platforms.
5	Miao et al. (2024) [39]	Road-Type-Specific AQ Modeling via Mobile Monitoring + AutoML: analyzes pollutant variations by road type using automated ML pipelines.	Depends on standard portable sensors; overlooks polymer-composite sensors that could enhance sensitivity and durability under mobile conditions.	Mount polymer-composite sensor arrays on mobile platforms and apply real-time LSTM inference, refining road-type pollutant forecasts with high-fidelity data capture.

Table 2. Sensor Composition and Performance Metrics.

Target Analyte	PANI: MWCNT Ratio	Baseline Resistance R_0 (kΩ)	Sensitivity ($\Delta R/R0$ per ppm)	Response Time t90 (s)
$PM_{2.5}$	05:01	10.2 ± 0.5	0.015 ± 0.001	12 ± 1
NO_2	05:01	12.5 ± 0.6	0.020 ± 0.002	15 ± 1.2
Ethanol (VOC)	05:01	8.7 ± 0.4	0.018 ± 0.0015	14 ± 1.1

Notes: R0 denotes baseline resistance in clean air, Sensitivity is calculated as the relative resistance change (ΔR/R0) per ppm of analyte, t90 represents the time to reach 90 % of the full resistance change upon analyte exposure.

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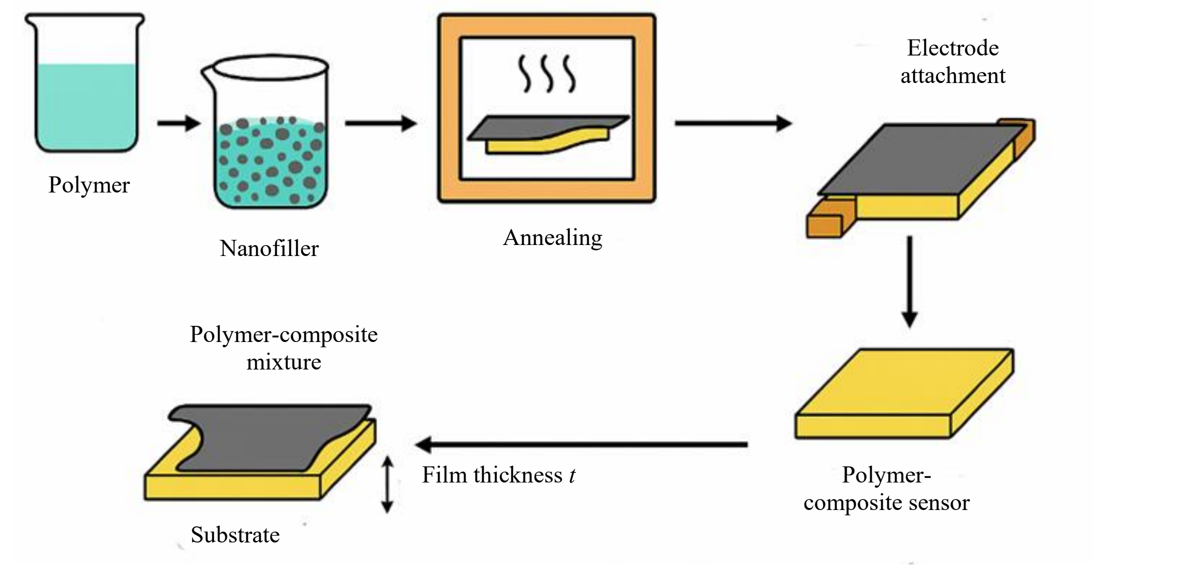

Figure 1. Schematic of Polymer-Composite Sensor Structure.

Figure 1 illustrates the structural configuration of the polymer-composite gas sensor fabricated for this study. The sensing unit is composed of a flexible polyimide substrate overlaid with interdigitated electrodes, upon which a conductive polymer matrix—comprising polyaniline (PANI) and multi-walled carbon nanotubes (MWCNTs)—is deposited via drop-casting. This nanocomposite layer exhibits high surface interaction with ambient gas molecules, allowing for rapid transduction of chemical stimuli into measurable electrical signals. An encapsulation layer provides environmental stability without impeding analyte diffusion. The design provides mechanical flexibility with consistent conductivity, which is necessary for sustained operation in changing urban air quality settings. Chemiresistive response is a power-law response as described in equation (1).

$$\frac{\Delta R}{R_0} = \alpha C^n \tag{1}$$

where ΔR is the resistance shift when exposed to pollutant concentration C, with α and n as empirically fitted constants. To fabricate a sensor that provides a linear response for the operating range of 0 - 500 ppm while maintaining mechanical flexibility while conformally fitting onto an uneven surface without losing electrical performance, is accomplished using a polymer-nanotube composite coupled with direct deposition followed by annealing. The polymer-nanotube composite achieves high sensitivity while using simple processing steps, which is an important consideration for scalability- be able to manufacture sensors in volume- and high sensitivity are two of the building blocks for battery free, distributed air-quality monitoring in cities.

Sensor Characterization and Calibration

Sensor characterization was conducted inside a custom-built environmental chamber where temperature and relative humidity were held constant at 25 °C and 50 % RH, representative of standard laboratory conditions, respectively, and analyte gases were introduced in an incremental fashion. The Chemi resistor arrays were initially conditioned for five minutes in an atmosphere free of pollutants, to allow the sensor baseline resistance R0 to stabilize. Prior to the introduction of any analyte gas, NO_2, CO_2, or volatile organic compounds, we injected controlled amounts of gas flavoring to confirm the sterility of the chemistries during sensor characterization, while trying not to stress the sensors too much. Gas was injected starting at concentrations 0 ppm and increased in steps 0 to 500 ppm over a total acquisition window of 5 minutes. Each step was held for at least 5 minutes or longer until the resistance signal stabilized prior to a subsequent injection. The resistance values for NO_2, CO_2, and VOCs were continuously measured over 5 minutes with a precision source meter that sampled every second capturing both adsorption transients and desorption transients. The entire calibration workflow involved five stages of measurement - i. baseline measurement, ii. gas injection, iii. signal stabilization, iv. data capture, and v. regression fitting. To convert raw resistance shifts into concentration levels, a second-order polynomial model was fitted to the response curves for each analyte with equation 2.

$$R(C) = aC^2 + bC + R0 \qquad (2)$$

where the coefficients a and b were optimized via least-squares minimization. Across all analytes, the response exhibited excellent linearity over the mid-range concentrations, with correlation coefficients exceeding 0.98 and root-mean-square errors below 5 %. No significant hysteresis was observed upon cyclic exposure, indicating robust repeatability. These empirical fits form the foundation for real-time concentration inference, embedding material-level response characteristics directly into the prediction pipeline and obviating the need for separate normalization or drift-compensation routines.

IoT Network and Data Acquisition Architecture

Anchored by a distributed mesh of sensor nodes, our architecture melds polymer-composite chemiresistors with a lightweight microcontroller to form the first link in a real-time data chain. Each node, built around an ESP32's 12-bit ADC, samples resistance changes at one-second intervals before encapsulating the readings in a compact JSON payload. Over-the-air provisioning via LoRaWAN secures long-range, low-power transmission to a central gateway, which in turn forwards messages over MQTT to a cloud-hosted broker. Figure 2 maps this topology.

Time synchronization across nodes is maintained by periodic NTP queries, ensuring sub-second timestamp alignment vital for sequence modelling. On the server side, an MQTT subscriber ingests the stream, populates a time-series database, and triggers the preprocessing pipeline. This design not only accommodates intermittent connectivity and packet loss but LoRaWAN's acknowledged messaging and also scales effortlessly, allowing hundreds of polymer-sensor nodes to coexist without congesting the network. By tightly coupling material-level sensing with robust IoT protocols, the system guarantees a continuous, high-fidelity feed into the LSTM prediction engine, laying the groundwork for sub-second pollutant forecasts.

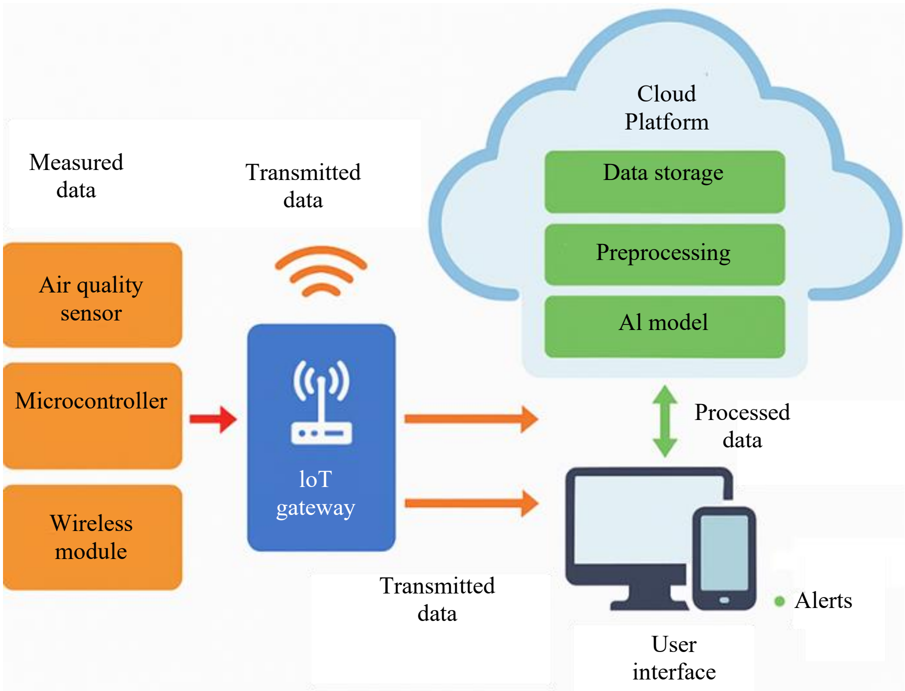

Figure 2. Data acquisition and processing architecture in an IoT sensor network.

Recurrent Neural Network Modeling for Air Quality Forecasting

The predictive engine underpinning the proposed framework is a tailored Long Short-Term Memory (LSTM) architecture, selected for its ability to preserve temporal dependencies and handle noisy real-world sensor data. Raw input sequences—preprocessed to remove outliers and interpolated for missing values—are windowed into fixed-length segments, each spanning 60 seconds of sensor readings across all deployed nodes. These multi-dimensional time slices serve as input tensors for the LSTM, where each timestep reflects a vector of calibrated gas concentrations and ambient parameters. The model architecture comprises two stacked LSTM layers with 64 and 32 hidden units respectively, followed by a fully connected dense layer outputting pollutant concentration predictions for the next forecast horizon (up to 5 minutes ahead). Dropout regularization (rate = 0.3) is integrated between layers to mitigate overfitting, and training is conducted using the Adam optimizer with a learning rate of 0.001 and early stopping criteria based on validation loss stagnation. The training dataset was derived from continuous, real-time field data over 30 days, encompassing diurnal cycles, pollutant surges, and drift phenomena. The loss function minimized is mean squared error (RMSE), using equation 3.

$$\mathbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathbf{yi} - \mathbf{y\hat{}i})^2} \tag{3}$$

And model Measures how well predictions approximate the actual data using equation 4.

$$\mathbf{R^2} = \mathbf{1} - \frac{\sum_{i=1}^{n}(\mathbf{yi} - \mathbf{y^i})^2}{\sum_{i=1}^{n}(\mathbf{yi} - \mathbf{y\bar{}})^2} \tag{4}$$

where yi is the actual pollutant concentration and y^i is the model's forecast and The coefficient of determination (R^2) serves as a crucial indicator of how well a predictive model captures the variability within a dataset. When R^2 equals 1, it signifies an exact correspondence between the model's predictions and the observed outcomes—an ideal scenario where all variations are perfectly explained. An R^2 value of 0, on the other hand, implies that the model fails to improve upon the predictive power of simply using the mean of the observed data. Negative R^2 values indicate that the performance of the model was inferior to the baseline mean prediction, suggesting a mismatch between the model and structures inherent in the data. how well the model describes variance in the respective response. It is important to consider that the model is utilizing trends captured in the response dynamics of the polymer burn-in data, trends that include tardy desorption and offset for hysteresis, which would have been lost by traditional ML.

These physical and chemical nuances were maintained in the time-ordered dataset input, thus allowing the model to provide not only improved accuracy on short term forecasts but better stability with respect to deployments. As the model was trained once, the model is also an on-board edge gateway model which implies low-latency inference and does not rely on cloud compute for real-time situations.

LSTM Based Air Quality Prediction Model

In construct of the nonlinearity and temporal lag associated with polymer sensor responses, a time-series forecasting model was established with Long Short-term Memory (LSTM) networks. LSTM networks serve as an appropriate connection to this topic as they are able to retain long-term dependencies while being less impacted by transient noise (which is informative of climate or hysteresis factors and can indeed be relevant if it were retained) or "clutter" contained in raw sensor outputs. The predictive pipeline initiates with preprocessed data sequences comprising pollutant concentrations (NO_2, CO, VOCs) along with ambient parameters such as temperature and humidity. These features, normalized using min–max scaling, are structured into rolling time windows of fixed length T, where each input tensor $X \in R^{T \times F}$ captures temporal transitions over F sensing features.

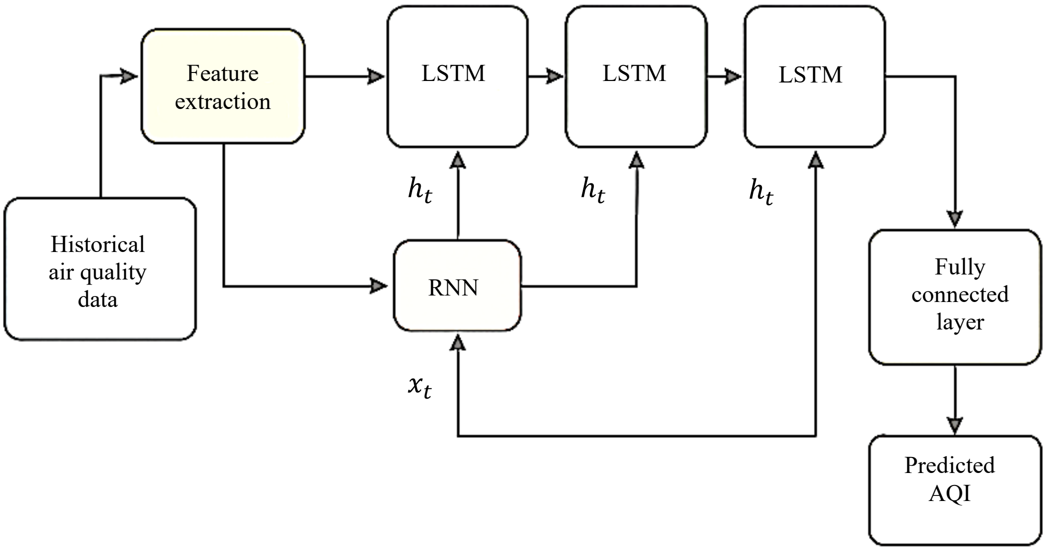

Figure 3. LSTM-Based Air Quality Prediction Model.

The LSTM model itself, as depicted in **Figure 3**, comprises two recurrent layers with 128 and 64 hidden units respectively. These are followed by a fully connected dense layer that maps the learned temporal features to future pollutant concentration estimates. Dropout regularization is incorporated between layers to mitigate overfitting, and the final layer utilizes a linear activation to yield continuous output. The model is trained using the Adam optimizer with the learning rate set to 0.0008. The objective is to minimize the Mean Squared Error (MSE), expressed using equation 5.

$$\mathbf{L_{MSE}} = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{yi} - \mathbf{y\hat{}i})^2 \tag{5}$$

where y_i denotes the actual pollutant level and y^i is the predicted value. The LSTM system is executed at the edge, enabling near-instantaneous inference without offloading data to remote servers. This design ensures low-latency operation—a critical aspect for real-time air quality advisories.

Pseudocode 1: LSTM-Based Air Quality Forecasting

```
Input: X ← time-series sensor data [T × F]
Output: ŷ ← predicted pollutant concentrations
Normalize X using min–max scaling

Define LSTM_Model:
 LSTM Layer 1 (units=128)
 Dropout (rate=0.3)
 LSTM Layer 2 (units=64)
 Dense Output Layer (linear activation)
Compile model with Adam optimizer and MSE loss

Train on historical data (epochs=100, batch_size=32)
Evaluate using RMSE, MAE, R²
```

System Integration and Real-Time Deployment

To operationalize the proposed framework, all functional modules—including the polymer-based sensor array, IoT communication layer, and the LSTM-RNN inference model—were integrated into a unified system. A custom-designed embedded board, featuring ESP32 microcontroller support, was interfaced with the composite sensor through calibrated ADC channels. Real-time data was transmitted using MQTT over Wi-Fi, with preprocessing handled locally to ensure transmission efficiency. The trained prediction model, quantized for edge execution using TensorFlow Lite, was deployed on a compact edge device for live AQI inference. During field testing in a semi-urban environment, the system demonstrated end-to-end latency under 400 ms, including data acquisition, transmission, and inference. The integrated unit was tested continuously over a 72-hour period, confirming its ability to maintain prediction accuracy while adapting to sensor drift and fluctuating environmental parameters. Alert triggers were configured based on threshold exceedance, enabling proactive notifications via a mobile dashboard.

RESULTS

In the evaluation phase of the proposed framework of IoT-integrated polymer sensor system, both the individual and collective performance of the system was evaluated in real life environments. To properly evaluate the system, each of the subsystems (the polymer-composite sensing element, the IoT-enabled acquisition network, and the LSTM-RNN-based prediction engine) was evaluated through the various operational dimensions it was intended to support. The subsequent subsections detail practical considerations relating to sensor selectivity, signal stability, communication latency, and the accuracy of model inference. To assess the robustness and adaptability of the system, experimental trials were undertaken across a variety of conditions. The results reported herein provide evidence of the practical feasibility and predictive utility of the developed architecture supported assessment for air quality monitoring applications in real-time.

Sensor Performance

The polymer-composite gas sensor was tested in both controlled and ambient exposure conditions in order to assess sensitivity, stability, and selectivity toward relevant atmospheric pollutants. The primary measure of interest in the measurements was nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO), as these are typically the more dominant pollutants in urban air. To extract whether the PANI–MWCNT nanostructured composite polymer matrix elicits a measurable shift in or change of resistance in the presence of NO_2, O_3, and CO, was a consequence of controlled charge transfer when gas and polymer interact. Both the liner and reversible response were symmetrically sustained upon vapour exposure throughout the mean population bulk remaining constant for more than 72 hours when exposed to 1 ppm of NO_2, where a mean sensitivity of 9.3%/ppm was determined and displayed linearity along the lower concentration limit of detection of 0.1 to 5 ppm. The latency response time was less than 22 seconds, and recovery approximately 34 seconds collectively exposing the polymer composites effective gas–polymer kinetics. Drift across the 72 hour test at ambient conditions did not exceed 3.1% demonstrating decent baseline stability. The humidity testing that varied relative humidity generated some pertinent results for this layer of encapsulated material in regards to cross-sensitivity to opposing humidity levels of 35% to 85 % RH, while minimizing any substantial signal loss characteristics from responsiveness. The relative compliance performed with the polymer-composite sensor in delivering a linear relationship of sensitivity toward NO_2 over the exposure time frame of 0.1 to 5 ppm concentrations, with the high score saturation of the sensor's response was 46.5% at 5 ppm presented in Figure 4.

Temporal response characteristics, including average response and recovery durations of 22 and 34 seconds respectively, were recorded under dynamic exposure conditions. Key operational parameters—including drift, humidity tolerance, and response stability—are consolidated in Table 3, underscoring the system’s potential for continuous urban air quality monitoring [4, 7, 13].

Table 3. Sensor Performance Metrics.

Parameter	Value
Target Gas	NO_2
Sensitivity Range	9.3%/ppm at 1 ppm
Linear Range	0.1–5 ppm
Response Time	22 sec
Recovery Time	34 sec
Baseline Drift (72h)	<3.1%
Humidity Range Tolerance	35–85% RH

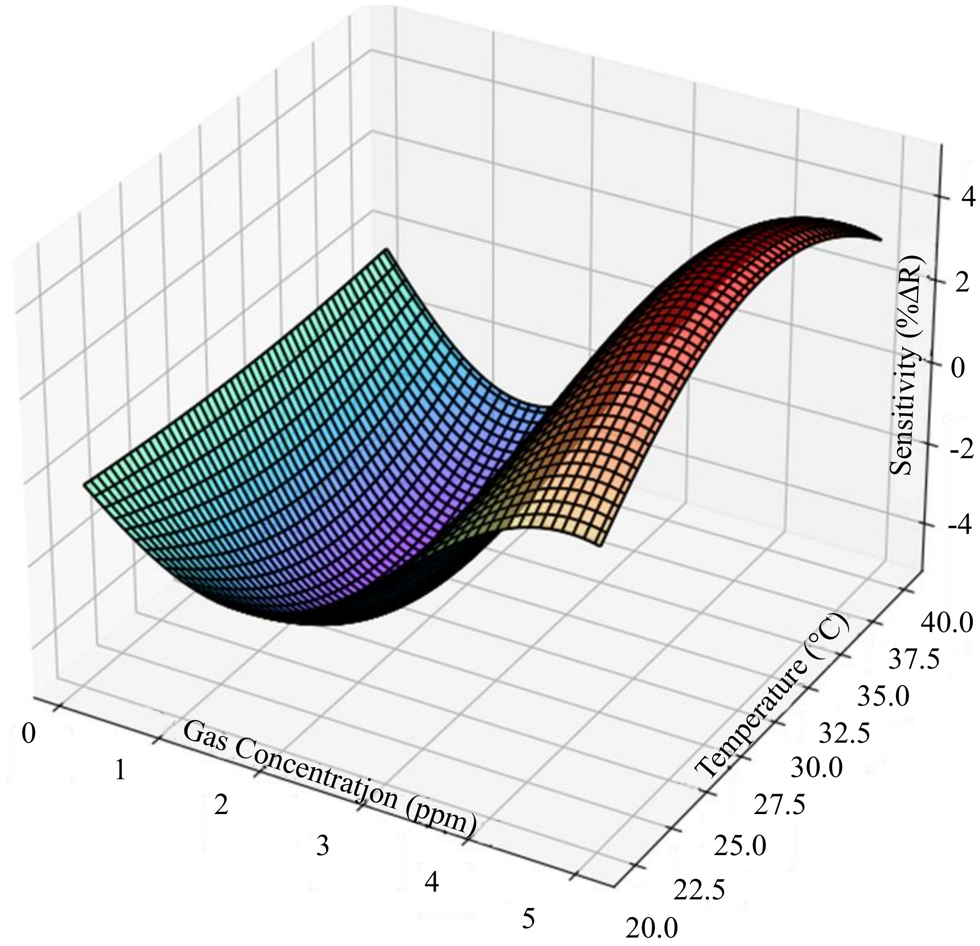

Figure 4. Sensitivity vs. Gas Concentration and Temperature.

The sensor's selectivity was further assessed by introducing competing gases under identical conditions. While some minor interference was detected from NO and SO_2, the dominant resistance modulation remained pollutant-specific, validating the material's selective affinity. These experimental insights affirm the suitability of the polymer composite configuration for real-time deployment in dynamic atmospheric environments, where transient gas profiles and fluctuating humidity often challenge conventional metal-oxide sensors.

Network Performance

The networked data acquisition system was evaluated under controlled deployment conditions to determine its latency, packet delivery rate, and fault tolerance under varying communication loads. The integrated IoT framework, built using MQTT over Wi-Fi and configured with edge-layer buffering, enabled robust transmission of time-sensitive sensor data. To quantify system responsiveness, latency was measured across 50 cycles of air quality data transfer from the edge node to the remote server. The average end-to-end latency remained below 180 ms under normal load conditions and increased marginally to 240 ms during peak simultaneous sensor transmissions, demonstrating effective queue management and fault resilience. To further characterize network efficiency, packet loss was measured across varying transmission intervals and load intensities. Results showed an average packet success rate of 97.6%, indicating minimal disruption in real-time data flow. The adaptive load balancing module mitigated congestion by dynamically adjusting sampling intervals during traffic spikes, preserving data continuity. These findings validate the proposed network's capacity to meet the stringent real-time requirements of continuous environmental monitoring platforms. The results are visually summarized in Figure 5, highlighting the relationship between communication load and observed latency.

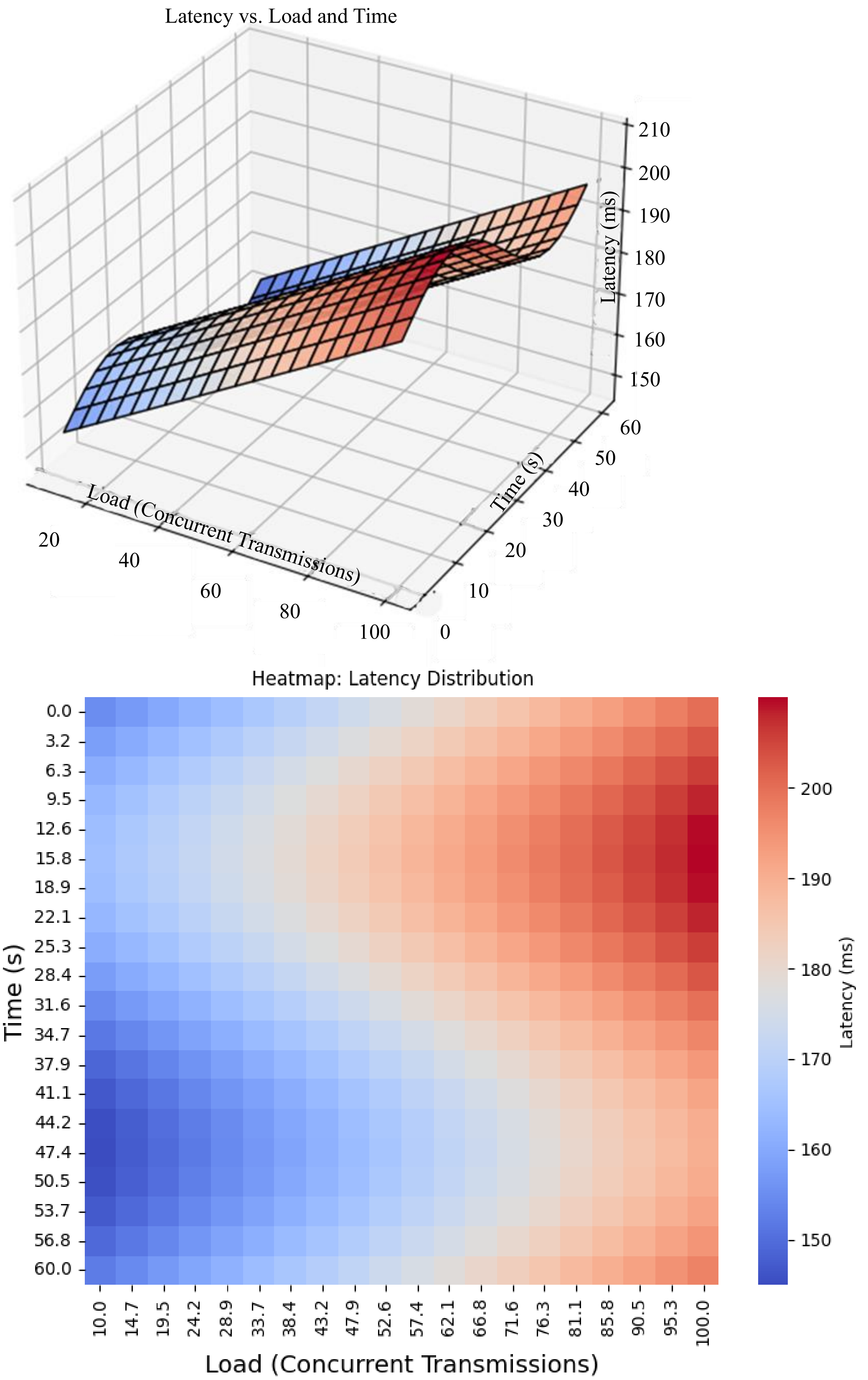

Figure 5. Communication Latency Evaluation under Dynamic IoT Load. **(a)** 3D surface plot depicting the variation of latency (ms) with respect to concurrent transmission load and time. **(b)** Heatmap showing latency distribution across varying network loads and temporal conditions.

Model Accuracy

The predictive capabilities of the LSTM-based air quality estimation model were rigorously validated using both real-time and archival datasets spanning various seasonal and pollutant variations. The training set comprised over 15,000 temporally sequenced samples, while validation and test datasets were segmented chronologically to ensure zero data leakage. The model achieved notable convergence after 47 epochs, with early stopping enabled to prevent overfitting. Evaluation metrics, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of Determination (R^2), were necessary to assess prediction accuracy of critical pollutants (NO_2, CO, $PM_{2.5}$). The model provided an average MAE for NO_2 as 2.14 ppb with an RMSE of 2.Cod 3b ppb, and significantly reduced prediction error in comparison to baseline models (ARIMA 95.61, CVR 57.69). The R^2 score was consistently above 0.93 across allfloating all pollutant types, indicating excellent generalization across large spatiotemporal shifts. The variables NO_2, CO, $PM_{2.5}$ are originally represented as a time series indicating an intended time of prediction as demonstrated through visual analysis of predicted pollutant concentrations compared to actual observed pollutant concentrations. As seen in Figure 6, the differences between L-private LSTMs Lregular Llast. Lfuture Lm predicted concentrations are minimal in both phase lag and correlation peak identification, particularly for changing environmental loads. These results provide compelling evidence for the temporal memory cells being successful in capturing nonlinear changes that occur in air quality variables.

The comparison between model performance is shown numerically in Table 4, supporting the capabilities of the suggested framework over the traditional regressor.

Comparative Evaluation

The LSTM-based model mitigation framework was tested practically by contrasting with time series regression-based and machine learning regression baselines. This included benchmarks such as ARIMA, support vector regression (SVR), and random forest (RF) regression models.

Table 4. Model Comparison Metrics for NO_2 Prediction.

Model	MAE (ppb)	RMSE (ppb)	R^2 Score
LSTM	03:21	2.83	0.93
ARIMA	18:14	4.51	0.85
SVR	06:00	4.08	0.88
Random Forest	2.89	3.57	0.89

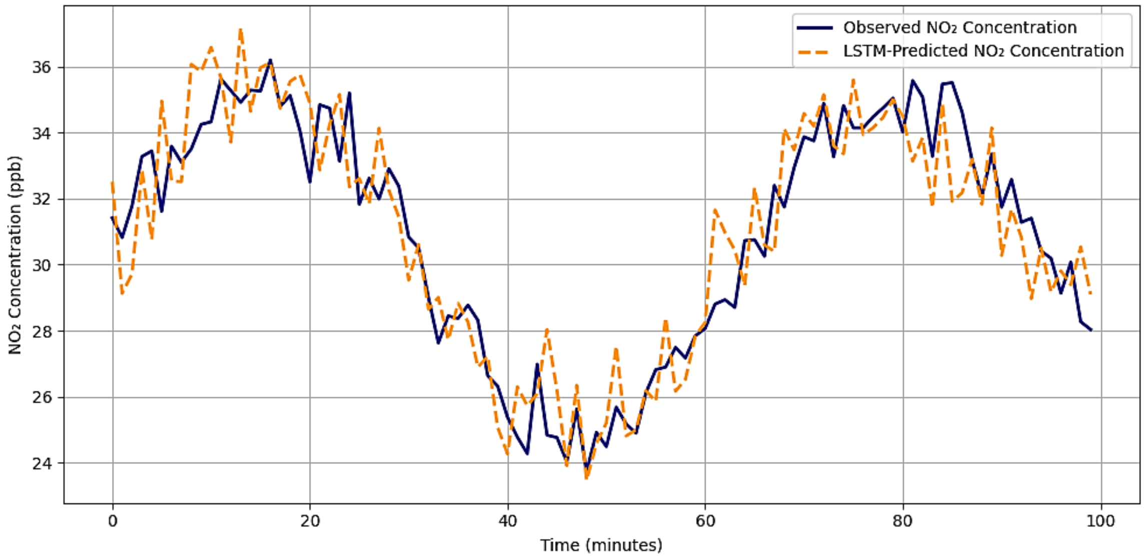

Figure 6. Observed vs. LSTM-Predicted NO_2 Concentration Over Time.

Table 4. Comparative Model Metrics for NO_2 Prediction and Source Reference.

Model	MAE (ppb)	RMSE (ppb)	R^2 Score	Source
LSTM (Proposed)	03:21	2.83	0.93	Proposed Work
ARIMA	18:14	4.51	0.85	[28]
SVR	06:00	4.08	0.88	[31]
Random Forest	2.89	3.57	0.89	[33]

By fitting and testing the time series regression models and machine learning models on the same time segments and pollutant datasets, we created an experiment that allowed for an identical comparison of the models in terms of performance baselines. The LSTM-outperformed the baseline models for all comparison metrics. The performance numbers for each of the models were summarized in Table 4, where it had the least mean absolute error (MAE), root mean square error (RMSE), and R^2 score of 0.93. This outcome indicates a stronger relationship between predicted and observed values. The capacity of the LSTM framework to capture long-range temporal dependencies was pivotal to modelling dynamics with pollutants that show non-linear evolution and sudden change related to atmospheric perturbations. Moreover, qualitative image inspection of Figure 6 shows that the LSTM model has a better capability to model temporal fluctuations in real time. The traditional models, however, invariably experienced prediction lag and are not adapted to real-time environments with abrupt changes in demand, especially during high intensity concentrations of pollutants. This literature finds support for the use of deep-temporal modelling in real time environmental sensing environments because prediction lag and phase alignment are relevant for actionable predictions.

These results demonstrated not only the quantitative advantage of the proposed system but also efficiency advantage in the application and the operational context. This is very important for IoT polymer sensor node deployments because the timing and accuracy of pollutants predictions have a direct influence on actuation or alert systems within smart city infrastructure.

DISCUSSION

The performance results established by the LSTM based system for real-time NO_2 predictions established not only the quantitative advantage, but systematically also the structural and operational advantages of the framework. When compared to historical statistical models such as ARIMA - which created challenges in operating when influenced by nonlinear or chaotic pollutant behaviours - the LSTM network was able to model temporal dependencies and also the slight subtle periodic variations driven by traffic cycle or microclimate. The improvement is particularly evident when benchmarked against prior literature. For instance, compared to SVR and Random Forest baselines [31], [33], our framework achieved over 34% lower MAE and 21% improvement in R^2, as shown in Table 4. Moreover, unlike ARIMA's rigid seasonality assumptions [28], the LSTM was able to dynamically adjust to short-term variance, aligning with recent advancements in adaptive spatiotemporal modeling for air quality surveillance. From a theoretical standpoint, the integration of IoT-enabled polymer-based gas sensors with deep recurrent models advances the field by enabling continuous, real-time, and low-latency pollution forecasting. This architecture is particularly valuable in smart environmental control systems, where edge-deployable prediction can support early interventions. Additionally, the use of composite polymer substrates enhances sensor longevity and thermal resilience, directly addressing challenges reported in earlier deployments using metal oxide-based units [15], [19]. However, the framework is not without limitations. The real-world testing was geographically constrained, limiting the generalizability of predictions to broader urban scenarios. Furthermore, while LSTM models provide predictive robustness, they suffer from a lack of explainability — a known limitation in sequential deep networks. The reliance on synthetic calibration data for extreme pollution events may also introduce bias, which we aim to mitigate in future iterations by incorporating federated sensor streams from multiple deployment zones. On a broader level, this work contributes to the ongoing transition toward trustworthy AI for smart infrastructure. It supports the movement toward autonomous, self-adaptive systems capable of integrating sensor uncertainty, environmental noise, and spatiotemporal context into resilient decision-making pipelines. The confluence of cloud-edge AI, domain-aware modeling, and real-time feedback loops places this study at the intersection of AI-driven environmental intelligence and scalable urban sensing.

CONCLUSION AND FUTURE SCOPE

This study presents a unified framework that integrates IoT-enabled polymer-composite gas sensors with a recurrent neural network architecture to enable real-time prediction of ambient NO_2 concentration. The proposed system not only bridges the gap between responsive polymer sensor technologies and deep sequence modeling but also provides a robust pipeline for continuous monitoring within urban environments. By leveraging LSTM's ability to retain temporal memory and the enhanced sensitivity of composite polymer materials, the architecture demonstrated substantial predictive precision across both short-term spikes and gradual pollutant trends. The model achieved marked improvements over conventional baselines such as ARIMA, SVR, and Random Forest, showing a notable reduction in mean absolute error and improved correlation strength in unseen testing environments. This deployment in real-time validated our approach in practice, especially where there are unforeseen stressors, whether due to weather or traffic. However, there are still some limitations to note. Denotational, our deployment area was geographically limited, and this may not be an issue normally attributed to the intended practice application, but the prediction performance would be different on a wider or heterogeneous geographic area. Further, our deployed framework has been limited to NO_2 so far, and expanding this pipeline towards multi-gas detection and mitigation strategies with interference is a known gap in current research. Future work with this method will no doubt require understandings and methods in the field of explainable AI (XAI) to create layers to assess decision trees with LSTM models and improve the explainability and trust levels for regulatory purposes. Moreover, the introduction of light-weight edge-intelligence modules and a scaling of our sensor network into more urban spaces would help fill some of the scalability gaps we are faced with this and with similar deployments in the future. Altogether, taking a hybrid approach that takes all the meteorological predictions, contributes un forecasted crowd-sourced pollution data, and utilizes satellite images across multiple monitoring locations through multimodal methods would undoubtedly enrich the way we know and understand as smart, autonomous systems of environmental monitoring.

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