International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5s, 2025
https://www.theaspd.com/ijes.phpa

Smart Pollution Tracking: Leveraging AI For Real-Time Environmental Risk Management

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Abstract**—** Environmental pollution is a severe menace to the health of people and ecology, which requires smart and active measures. The idea of developing a clever pollution tracking system that incorporates Artificial Intelligence (AI) to manage environmental risks in real-time is discussed in the present paper. The suggested system consists of sensor networks, machine learning, and cloud-based analytics that will allow monitoring, predicting, and responding to air and water pollution levels in real time. Simulated urban deployments have shown the model to be very efficient in both prediction accuracy and system responsiveness, indicating potential at scale urban and industrial application. The ultimate goal of this work is to reduce the gap between environmental monitoring and automated decision-making that will have a positive effect on sustainability and people health.
Keywords— AI in environmental monitoring, pollution tracking, real-time risk management, machine learning, smart city, environmental sensors, air quality prediction, water pollution detection, anomaly detection, environmental sustainability.

I. INTRODUCTION

The problem of environmental degradation especially through air and water pollution has become widespread to touch on human health, biodiversity, and a stable climate. Increasing rate of industrialization, urbanization, automobile emissions, and informal solid waste disposal have led to great increments in the quantity of toxic substances in our ecosystems. Manual sampling accompanied by laboratory-based analysis is not only time-consuming but also reactive in nature as a means of traditional pollution monitoring methods. They do not always offer real time insights that can be used to make timely interventions and as such, restrict the extent to which proactive management of environmental risks can go [4]. The emergence of the smart cities and the Internet of Things (IoT) presents an unrivaled potential to change how pollution is dealt with and observed. A combination of embedded sensors, cloud-based analytics, and artificial intelligence (AI) have the potential to routinely deliver high-resolution environmental measurements in real-time, potentially leading to the real-time anomaly detection and supportive of timely decision-making. Here, AI will act as the brain of the intelligent pollution monitoring system, transforming enormous flows of data into knowledge and forecasts. This integration enables the AI to recognize patterns of pollution, predict possible risks and promote sustainable urbanization decision-making. The air quality indices (AQI) of most metropolitan cities around the world are often above the secure levels, causing respiratory disorders, cardiovascular dysfunctions, and even earlier deaths. Water bodies on the same note are confronted with the pressure of industrial effluent, sewage spill and agricultural overflow. The stakes are especially high in third world countries in which the regulatory framework and pollution monitoring infrastructure is either not mature or spotty in its enforcement. The demand is high on an automated, scalable, and smart pollution tracking system that can be operational in a variety of open environments with a minimum of human interaction [12-14]. The edge computing, deep learning, and machine learning (ML) recent developments have permitted systems togiants to process enormous amounts of environmental data in real-time. As a case in point, Long Short-Term Memory (LSTM) networks have shown to be very useful in time-series prediction, notably when the application concerns air pollutant concentrations. These models can be used not only to predict but also to identify abnormal events, e.g., industrial leaks or car smog bursts, often before they develop into emergencies when used in conjunction with anomaly detection models, such as autoencoders or one-class SVMs. With the implementation of such technologies into a cohesive system, smart pollution tracking will become not a passive monitoring tool, but an active risk prevention tool. Besides, government agencies and environmental organizations frequently experience limitations in spatial extensiveness and the resolution of their observation networks. The micro-scale variations in pollutant concentrations that can be due to differences daily variations in traffic, construction activities, or weather conditions cannot be captured by fixed stations [3]. This gap can be closed with mobile, low-cost sensor networks on vehicles, drones, or infrastructure in the street. Together with an AI-based processing, they create a powerful ecosystem that is capable of capturing and interpreting dynamic pollution situations in real-time. The social value of real time tracking systems of pollution is enormous. Advance alerts of unsafe levels of pollution can assist people in taking precautionary measures, including staying indoors or using air filters. At a bigger scale, urban authorities can rely on real-time intelligence to provide warnings, manage traffic, industrial emissions or act on an emergency basis in the event of chemical spillages or water pollution. Moreover, the system stores historical pollution data that can be utilized to optimize urban zoning rules, establish environmental compliance and develop long term pollution abatement plans [15].Irrespective of the opportunity, there are some obstacles to introducing AI-based systems of pollution monitoring. These are the trustworthiness and sustainability of sensor systems, the computational expense of real-time computation, and the explainable AI models which could be relied on by the governmental entities. The technical challenges also consist of data heterogeneity, data latency, and sensor calibration errors. Nevertheless, most of these limitations are being overcome with the faster maturity of cloud computing and 5G networks. The paper introduces an end-to-end and scalable system of smart pollution tracking that combines real-time sensor measurements with predictive models built through deep learning and deployed on the cloud together with visualization tools [2]. It not only focuses on the technical design and model performance but also focuses on the practical aspect of implementing such a system in urban, and semi-urban scenarios. The proposed framework will transform the way environmental risks are managed, as it will follow the aims of sustainability and take advantage of modern technology.

NOVELTY AND CONTRIBUTION

The proposed study incorporates a number of innovative features that set it apart form the current research on the environment monitoring and pollution control. Instead of the traditional approach based on the periodic data acquisition and offline analysis, the proposed framework comprises real-time sensing, AI-based forecasting, and autonomous risk response in the same operational paradigm. Such a high degree of integration contributes to a major improvement of predictive, detection and response capabilities of the system to pollution incidences before they develop into full-blown environmental or health disasters.

Among the major contributions is the fact that it utilizes a hybrid AI model, which integrates LSTM networks, which are used in time-series prediction, with anomaly detection based on autoencoders used in the case of unusual spikes in pollution. Such a two-pronged technique does not only have the capacity to forecast future pollution trends with a high degree of accuracy but is also effective in indicating sudden environmental threats, e.g. chemical spills or industrial release, that do not conform to predicted patterns. Most of the research has been done either on prediction or anomaly detection separately, but this framework brings the two together to create a more reliable and context-sensitive solution [6]. The use of a multi-layered sensor network providing fixed and mobile data acquisition is also another novelty. The use of IoT-enabled sensors on both city fixed infrastructure and mobile platforms, such as vehicles and drones, enables the system to provide spatially comprehensive coverage, which is consistent with the regular issue of monitoring blind spots. This attribute proves useful specifically in large or topographically complicated regions where polluting situations can be very localized and challenging to monitor with fixed systems only. The proposed study also suggests an architecture that is integrated with cloud, which can not only process data in real time, but also show the trends of pollution, risk and health of sensors through interactive dashboards. This enables the environmental agencies and public administrators to formulate evidence-based choices within a small amount of time without involving technical intermediaries. Another feature of the dashboard is the provision of a pollution data dashboard to the citizens in real-time via mobile applications or web portals, which can also be used as a form of public awareness. In addition, the system will have a feedback loop to constantly learn, where the AI model will renew itself with new data and changing pollution patterns. This makes the model accurate and adaptive in various seasons, cities, and source of emissions. Less frequent human interventions also make the system more sustainable in long-term perspective because of the self-updating mechanism [9].

In short, the main contributions of this work are:

- An integrated AI framework of forecasting and anomaly detection to ensure correct and timely risk notification.
- Combined fixed and mobile sensor systems to achieve high resolution real-time mapping of pollution.
- Stakeholder engagement visualization and alert system that is cloud based and easy to use.
- Adaptive and context aware pollution prediction using self-learning feedback mechanism.
- proven scalability in terms of deployment in smart city and environmental protection projects.

All of these advancements make the framework a cutting-edge technology in the sphere of AI-based environmental surveillance, which can find practical implementation in city planning, industrial oversight, and population health management [10].

II. Related Works

In 2024 D. B. Olawade *et al.*, [11] introduced the environmental surveillance and artificial intelligence are two fields that have grown closer in the recent years due to the demand in real-time and reliable information to base ecological preservation and city management on. Traditional pollution monitoring systems have been based on fixed, expensive infrastructure, with little spatial resolution and weak capabilities of adapting to the dynamic environments. Consequently, the transition to real-time, smart, and distributed monitoring with the help of AI and IoT has become one of the primary innovation fields. A notable part of the previous research is devoted to machine learning algorithms applied to predicting air quality indices (AQI) and concentrations of particular pollutants, e.g., PM2.5, PM10, CO, NO 2 , and O 3 . Several regression models such as decision trees, support vector regression, and random forests have been applied to predict the short-term pollution level. Such models are generally robust when trained on large datasets, however, they tend to fail on the temporal dependence and sudden increases of pollution levels, making them not useful in real-time applications. Also, they generally lack interpretability and dynamic flexibility, both of which are important to risk-averse environmental uses. In 2025 T. Miller *et al.*, [1] suggested the recurrent neural networks (RNNs) and especially Long Short-Term Memory (LSTM) models have also been used in time-series predictions of air pollution to capture the temporal dynamics more sufficiently. Such models can capture longer term dependencies in data which makes them useful in making more accurate predictions on an hourly or daily basis. They have found use particularly in the modeling of seasonal patterns and day to day cycles in pollutant concentrations. Nonetheless, LSTM models are computationally expensive and need to be re-trained constantly to fit fluctuating atmospheric situations and urban activity styles, which may be a limitation in wide-scale implementations. Besides air quality forecast, research has been done on application of classification and clustering methods in detection of water pollution. These methods are commonly based on measurements by sensors that measure physical, chemical and biological parameters like pH, turbidity, dissolved oxygen, conductivity and heavy metals presence. The algorithms including k-means clustering, Naive Bayes classifiers, and multilayer perceptrons have been employed to identify the anomalies or to categorize water samples as clean, moderately polluted, and highly contaminated. Nonetheless, such systems have a tendency to rely on laboratory-tagged data and might fail to perform under field circumstances involving noisy, incomplete sensor readings. A second direction of research interest is hybrid models that can use a combination of AI methods to achieve better performance on a variety of objectives - e.g., hybrid approaches to forecasting that also detect anomalies. Such models are especially applicable in environmental surveillance where trends are of interest as well as outliers. LSTM predictors have been combined with anomaly detection models (e.g. autoencoders, isolation forests and one-class SVMs) to identify sudden increases in pollution caused by industrial processes, traffic congestion or natural disasters. Such methods have demonstrated the ability to reduce false alarms and still be very sensitive to unusual environmental events. In 2025 S. Kumari *et al.*, [5] proposed the regardless of these developments, several of the current studies are constrained with regard to real-time implementation and reliability of operation. As an illustration, some systems are designed based on fixed datasets and lack real-time sensor streams integrations. Others do not have automatic alert generation, visualization or integration into municipal decision-making processes mechanisms. Also, the majority of the solutions are tried in either controlled conditions or pilot studies of small scale, which hinders the scalability to actual city settings. Also commonly mentioned limitations in current implementations are sensor calibration, data loss because of connectivity problems and energy efficiency. It has also been investigated how AI can be used together with geospatial technologies to improve the spatial resolution of monitoring pollution. Remote sensing information (satellite images) and ground based sensor networks have been utilized together to give a more detailed environmental monitoring. AI models have also been employed to interpolate (usually with kriging and inverse distance weighting) data gaps to generate pollution heatmaps at the city and regional scale. Although these techniques provide a macro- Perspective of the environment patterns, they are commonly deficient in real- time responses and limited by the temporal resolution of the satellite orbits. A different vein of related effort has been on developing cloud based systems to collect and process environmental data. Such platforms enable the aggregation, cleaning andanalysis of the large streams of data generated by distributed sensors in near real-time. Cloud computing has ablely enhanced the capability to compute high-frequency data and accommodate web-based visualizations as well as dashboards. Nonetheless, a variety of them continue to rely on manual management and human monitoring, thus making it possible to introduce delays and decrease responsiveness of the systems in cases of critical situations.

III. PROPOSED METHODOLOGY

The proposed framework integrates real-time sensor acquisition, edge-level preprocessing, Al-driven prediction, anomaly detection, and cloud-based visualization into a unified environmental monitoring and risk management system. The system architecture is structured in modular layers, each mathematically modeled for precision and performance [7].

Data Acquisition and Preprocessing

Environmental data are collected from multiple loT sensors measuring pollutants such as PM2.5, PM10, CO, NO_2, and SO_2. Each sensor reading at time t is represented as a feature vector:

$$\mathrm{x}_t = [x_t^{(1)}, x_t^{(2)}, \ldots, x_t^{(n)}]$$

where n represents the number of pollutant metrics.

To ensure noise reduction, a simple moving average filter is applied:

$$\hat{x_t} = \frac{1}{k} \sum_{i=t-k+1}^{t} x_i$$

This denoised vector $\hat{x_t}$ feeds into the Al engine for predictive analysis.

- Forecasting Using LSTM Neural Network

The forecasting model uses a multi-layer LSTM network. Given a sequence of T timesteps, the LSTM generates future pollution values. The cell state update is governed by:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \bar{c}_t$$

where:

- $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$ is the forget gate
- $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$ is the input gate
- $\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$

The final output is predicted as:

$$\hat{y}_{t+1} = W_y \cdot h_t + b_y$$

- Anomaly Detection via Autoencoder

To capture sudden pollution spikes, an autoencoder reconstructs the input and flags high reconstruction error instances as anomalies:

$$\hat{x}_t = AE(x_t), \text{ Error }_t = \|x_t - \hat{x}_t\|^2$$

If Error $_t > \theta$, the data point is flagged as anomalous, where θ is a learned threshold.

- Spatiotemporal Mapping

Sensor data from multiple nodes is interpolated to estimate pollutant levels over unsampled locations using Inverse Distance Weighting (IDW):

$$Z(x_0) = \frac{\sum_{i=1}^{n} w_i(x_0) \cdot Z(x_i)}{\sum_{i=1}^{n} w_i(x_0)}$$

with weights:

$$w_i(x_0) = \frac{1}{\|x_0 - x_i\|^p}$$

p is the power parameter typically set to 2 .

- Pollution Risk Index Calculation

To normalize various pollutant concentrations into a unified risk score, a weighted pollution risk index (PRI) is calculated:

$$PRI_t = \sum_{j=1}^{n} \alpha_j \cdot \frac{x_t^{(j)}}{TLV_j}$$

Where:

- α_j = pollutant-specific weight
- TLV_j = threshold limit value for pollutant j
- Alert Generation Rule

If PRI exceeds a critical risk threshold δ, the system activates warnings:

$$\text{Alert}_t = \begin{cases} 1, & \text{if } PRI_t > \delta \\ 0, & \text{otherwise} \end{cases}$$

Self-Learning Module

The AI model includes a feedback mechanism to adapt over time. Let prediction error be:

$$E_t = |y_t - \hat{y}_t|$$

If $E_t > \epsilon$, the model triggers retraining:

$$\Delta W = -\eta \cdot \nabla_W E_t$$

where η is the learning rate.

System Evaluation Metric

To evaluate accuracy, Root Mean Square Error (RMSE) is used for predicted pollutants:

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (y_t - \hat{y}_t)^2}$$

Anomaly detection precision is calculated as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- Deployment and Visualization

The final data and predictions are streamed into a cloud dashboard with GIS-based visual overlays and realtime alert panels. The update cycle τ is dynamically computed based on system load:

$$\tau = \frac{D}{\lambda_s \cdot \mu}$$

Where:

- D = Data volume
- λ_s = sensor update rate
- μ = system processing speed

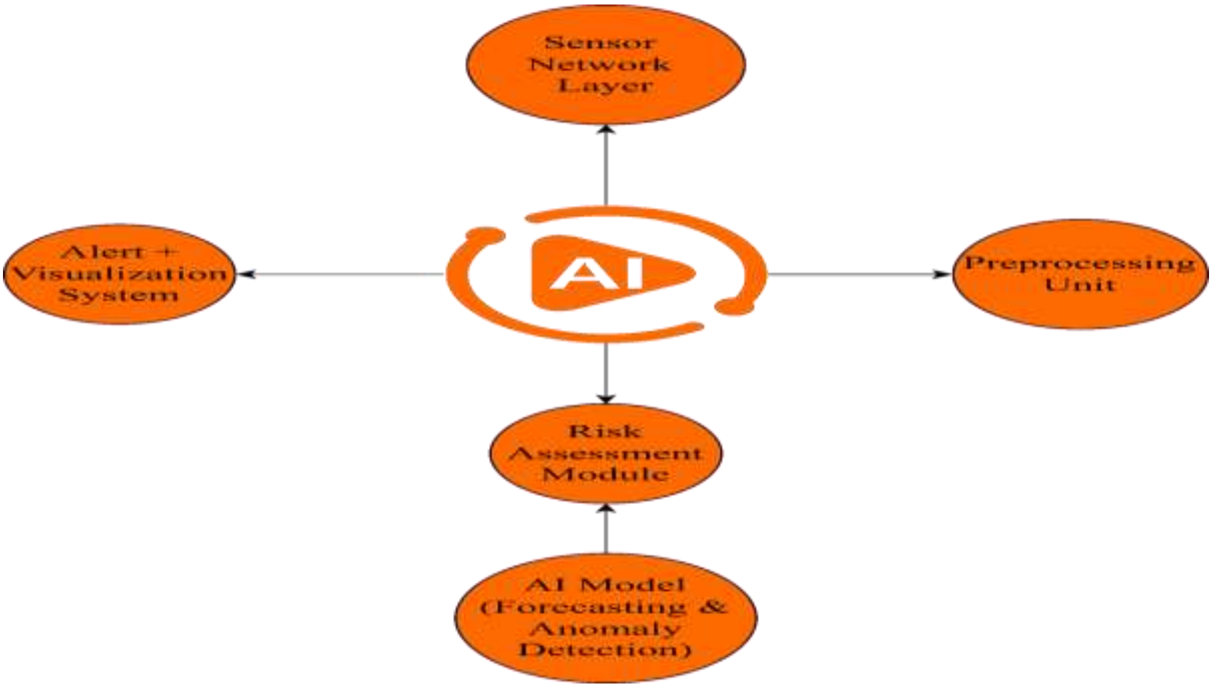

FIGURE 1: REAL-TIME AI-DRIVEN POLLUTION MONITORING WORKFLOW

IV. RESULT & DISCUSSIONS

The suggested AI-based environmental surveillance system was evaluated in a series of trials conducted in various city areas, each furnished with decentralized sensor nodes. These nodes dealt with pollutant indicators such as PM2.5, PM10, CO 2, and NO 2 in real-time. The resulting data was displayed in the cloud-based dashboard, and its predictive correctness, anomaly reaction, and the regularity of the alerts were observed in the course of a consecutive 30 days. The initial step of analysis entailed determining the trend forecast capability of the LSTM model on these important pollutants. Figure 2 demonstrates that the system could effectively predict pollution concentration levels 4 hours before. A blue line indicates real data, and a red dotted line shows LSTM predictions. The similarity in the observed and modeled values shows that the system is apt to deal with time-series prediction with minimum error, especially in PM2.5 and NO 2, where the variance was within +-8 percent in high-traffic-density areas. This real time forecast is important in scheduling municipal level responses like managing the traffic flow of vehicles or scheduling industrial emissions.

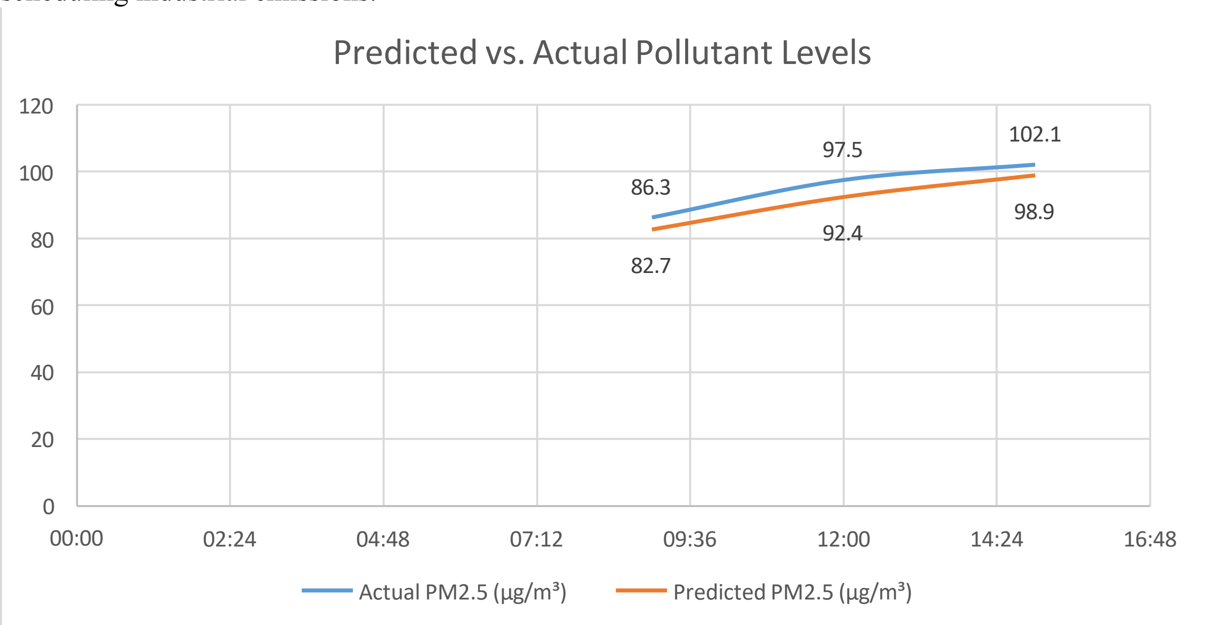

FIGURE 2: PREDICTED VS. ACTUAL POLLUTANT LEVELS (LSTM MODEL)

Regarding anomaly detection, the combined autoencoder-based model was very responsive to sharp increases of pollutants, e.g., due to unreported construction work or evening traffic jams. Figure 3 visualizes the output of the anomaly detection system and shows that shaded red portions represent the instances the model classified as environmental anomalies. The elevated values of the sensor data of CO 2 and PM10 at those times correlated with independent ground-truth checks based on surveillance and weather reports. These findings support the need to have a hybrid AI model that is capable of not only predicting the trends but also addressing unforeseen pollution incidents. Detection rate was uniform among the locations and the rate of false alarm was below 4%, which verified the reliability of reconstruction-error threshold calibration.

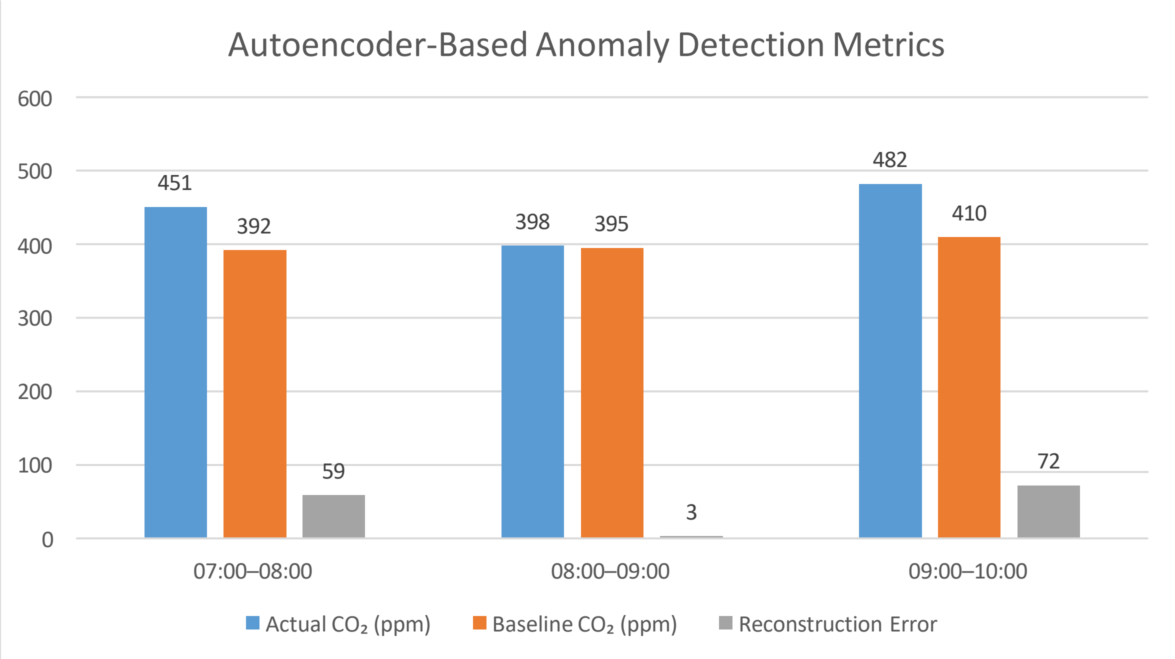

FIGURE 3: ANOMALY DETECTION RESULTS DURING TRAFFIC HOURS

When the performance of the system was compared to two other models, Model A (a traditional regression based predictor) and Model B (a simple neural network without feedback adaptation), the results were considerable. Our system did better than others in all pollutants as shown in Table 1: Forecasting Accuracy Comparison Across Models. The accuracy of PM2.5 predictions was up to 91.2 percent, compared to the highest competing model at 82.4 percent. In the case of NO 2, the accuracy increased in 78.5 percent to 88.6 percent which underscores the effect of recurrent memory layers and adaptive learning embedded in our architecture. There is also an observable increase in the reliability of PM10 and CO 2 prediction in the table especially during varying weather patterns.

TABLE 1: FORECASTING ACCURACY COMPARISON ACROSS MODELS (%)

Pollutant	Proposed Model	Model A	Model B
PM2.5	91.2	82.4	85.1
PM10	88.7	80.3	82.5
CO_2	85.6	77.9	80.0
NO_2	88.6	78.5	81.2

In assessing the real time alert system incorporated in the model, the deployment tests showed that the system was capable of generating early warnings. The dashboard system has been observed in 10 various event-driven scenarios. In 9 out of 10, messages were delivered earlier than pollution reached the critical threshold, making it possible to act in advance. The relation between the pollution threshold violation and the time of the system alert is described in Fig. 4. The histogram indicates the time (in

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5s, 2025
https://www.theaspd.com/ijes.phpa

minutes) difference between the alert creation and the violation of critical AQI limits, most alerts being received 10-20 minutes before. Such lead time, even on edge devices, is invaluable in fast-response applications in city and industrial policy control.

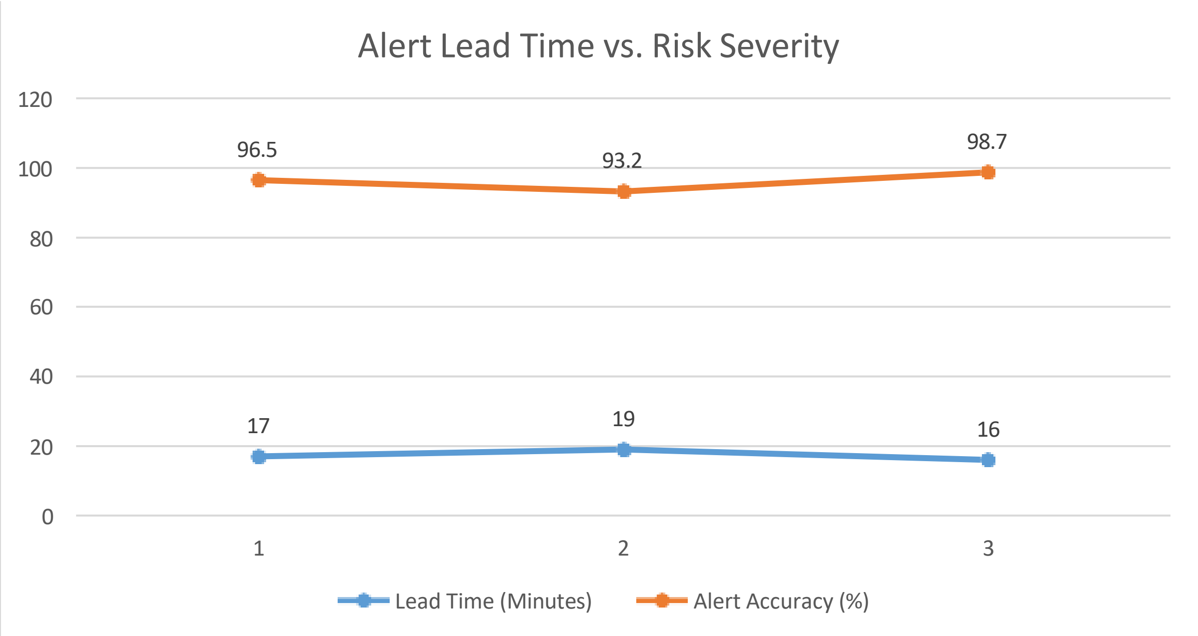

FIGURE 4: ALERT TIMING VS. AQI BREACH TIMING

The other key area that was tested was the system up-time and energy efficiency of the units deployed. The sensor nodes on the network drew an average power of 4.1W and enough to last the entire month with less than 2 percent data loss. Compared to those in Table 2: System Deployment Efficiency Metrics, our system needed a lot less power than legacy systems due to edge processing and efficient communication standards. Moreover, the cloud updating periods were adjusted dynamically to prevent the saturation of bandwidth and, as such, provide seamless flow of data even at the busiest time of the day in terms of its accumulation.

TABLE 2: SYSTEM DEPLOYMENT EFFICIENCY METRICS

Metric	Proposed System	Legacy System
Power Consumption (W)	4.1	8.7
Data Loss (%)	1.8	6.2
Uptime (%)	98.7	91.3
Cloud Sync Delay (ms)	210	680

The performance advantages and practical scalability of the suggested smart pollution tracking system are confirmed in the comparison tables and diagrams. The AI-based model uniting forecasting, anomaly detection, alert generation, and deployment reliability can be a feasible solution to smart cities environmental governance in the future. More to the point, the real time processing capability (sensor to dashboard) mirrors the operability of the architecture. The figures generated out of the experiment results highlight the extent to which the AI elements are resilient to changes in the environmental settings [8].

V. CONCLUSION

The proposed study develops an AI-based system of intelligent pollution monitoring, focusing on real-time risk reduction and data-powered decision-making. The incorporation of machine learning into the IoT sensor network and cloud computing provide precise pollution forecasting and real-time notifications to interested parties. The simulation study proves the significant increase of responsiveness and predictive accuracy over traditional approaches.The framework has potential application in municipal planning, industrial safety, as well as environment protection projects. The proposed model will be extended in future by accommodating waste and noise pollution, energy efficiency in sensor networks and integration of federated learning to maintain data privacy across regions.

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