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Research paper

Cloud-Native Framework for Urban Noise and Air Pollution Analysis

V. Thamilarasi [1] *, G. Sivaraman [2], S. Vijayalakshmi [3], Dr. R. Rajesh [4]

[1] *Assistant Professor of Computer Science, Sri Sarada College for Women (Autonomous), Salem, Tamilnadu, India*
[2] *Assistant Professor of Computer Applications, M.G.R. College (Arts and Science), Hosur, Tamilnadu, India*
[3] *Assistant Professor, Department of Computer Science and Technology, SNS College of Technology , Coimbatore, Tamil Nadu, India*
[4] *Assistant Professor of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R & D Institute of Science and Technology, Avadi, Chennai*
**Corresponding author E-mail: tamilomsiva@gmail.com*

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Abstract

Rapid urbanization, industrialization, and vehicle emissions all contribute to the widespread environmental and public health problem of urban air pollution. Because of their low spatial-temporal resolution and dependence on static sensor networks, conventional air quality monitoring systems frequently fall short in providing the high-resolution, real-time data required for environmental management and well-informed decisions. In order to achieve scalable, economical, and high-resolution environmental monitoring, this dissertation offers a thorough framework for an Internet of Things-enabled urban air quality monitoring system that combines multi-layer sensor architectures, sophisticated communication protocols, and predictive analytics. This study shows that the suggested framework is effective in attaining notable improvements in spatial-temporal resolution and prediction accuracy when compared to current systems through thorough testing and implementation in urban settings. The framework's ability to pinpoint pollution hotspots, predict air quality indices, and offer useful information to legislators and urban planners is demonstrated by case studies carried out in urban regions. The results also emphasize how important user accessibility, system interoperability, and data security are to the expansion of IoT-based monitoring systems for widespread usage. This study presents a cloud-native architecture for real-time noise and air pollution analytics, leveraging IoT technology and cloud computing to enhance urban environmental monitoring. The system collects and analyses data on various pollutants and noise levels, providing timely insights for effective decision-making and improved public health. By integrating AI-driven analytics and IoT sensors, this innovative approach enables scalable, secure, and data-driven urban planning strategies. This study advances the state-of-the-art in IoT-enabled air quality monitoring systems, adding to the expanding corpus of information on sustainable urban development. In addition to addressing important technological issues, the suggested strategy offers a way to combine environmental monitoring with smart city projects, promoting more sustainable and healthy urban settings. To improve the system's scalability and usefulness even more, future research topics include integrating policy-driven frameworks, cross-sector IoT applications, and adaptive artificial intelligence algorithms.

Keywords: *Environment; Pollution Prediction; Artificial Intelligence Algorithms; Cloud; Sensor Architectures.*

1. Introduction

A pollution-free and hazard-free environment is vital to human welfare and the sustainable development of any nation. Constant environmental monitoring (EM) is essential to safeguard public health and promote national progress. EM encompasses diverse activities such as pollution control, disaster management, and early warning for adverse natural and man-made conditions, including water contamination, air pollution, hazardous radiation, weather fluctuations, and earthquakes. Its primary objective is to address and mitigate environmental degradation to ensure a healthier world and sustainable civilization. In the context of smart cities, the integration of information, communication, and sensor technologies enhances resource management and service delivery across sectors such as healthcare, environmental protection, law enforcement, and community development [1].
Air pollution poses one of the most severe threats to the environment and human health, particularly in densely populated urban regions. Traditional air quality monitoring techniques often lack the predictive capacity and spatial granularity needed for effective pollution management. To overcome these limitations, the concept of an air quality digital twin has emerged—an advanced system that integrates real-time data from multiple sources such as industrial emissions, traffic patterns, weather data, and environmental sensors to generate a dynamic and accurate representation of air quality conditions [2]. Modern sensor networks, especially wireless sensor networks (WSNs), play a

crucial role in smart cities, as they enable the efficient collection and transmission of environmental data with minimal power consumption and maintenance costs. WSNs support multiple urban functions, including pollution reduction, waste management, traffic optimization, parking monitoring, and structural health assessment.

With the rapid advancement of technology, traditional environmental monitoring systems have evolved into Smart Environmental Monitoring (SEM) systems. SEM leverages cloud connectivity and intelligent sensor networks to measure environmental parameters more precisely and to minimize pollution and related adverse effects [3]. Cloud-integrated WSNs have shown great promise in monitoring and controlling variables such as vehicle emissions, temperature, and waste accumulation, thus enabling data-driven decision-making for sustainable urban management [4].

Among various environmental concerns, air pollution remains a critical issue that affects urban sustainability, public health, and economic growth. Using WSNs connected through cloud infrastructure, air pollution can be monitored more accurately and continuously across different city zones. This research builds upon this technological potential by proposing an IoT-enabled environmental pollution analysis framework based on WSNs, where sensor nodes installed in vehicles, buildings, and public transport systems continuously collect and transmit data related to air pollutants such as smoke and gases.

Despite the widespread adoption of IoT-based monitoring in general urban settings, a significant research gap exists in applying such systems to high-pollution industrial environments, where emission dynamics differ markedly from ambient urban conditions. The primary novelty of this work lies in the development and real-world validation of an IoT-enabled air quality monitoring framework within a specific, high-pollution industrial context—chrome plating—a sector largely neglected by prior studies.

2. Review of Literature

Pollutant concentrations have decreased in many places as a result of international efforts, but in many places, they are still higher than national criteria and World Health Organization (WHO) recommendations. This ongoing problem emphasizes the necessity of finding practical ways to reduce air pollution. According to Nazmul Hoq et al. (2019) and Solimani et al. (2019), air pollution is a contributing factor to several health problems, such as respiratory complications, heart and lung disorders, premature death, and negative community impacts that might result in mental health concerns. Reducing health hazards requires prompt access to information on air quality and preventative actions [6]. As a result, air quality monitoring has become essential (WHO TEAM, 2016). As a result, air pollution presents serious public health issues and has a number of detrimental effects on both the environment and human health. According to Zhang et al. (2014) and Yamamoto et al. (2014), prolonged exposure to poor air quality causes lung cancer, strokes, cardiovascular and pulmonary disorders, and a high global mortality rate. Because air pollution is responsible for a significant number of premature deaths, developing countries are especially at risk. Its effects are felt even in industrialized nations, where a sizable portion of the populace is exposed to dangerous situations (WHO TEAM, 2016) [7]. Sneezing, headaches, light-headedness, and eye irritation are among the short-term consequences. Additionally, recent studies have connected air pollution to infertility.

In the past, researchers have tested and studied many air pollution monitoring technologies. The objective of the system's creation was to automatically analyze the environment and employ intelligent technologies to do so, as we move closer to a more intelligent system every day. "A Real-Time Industrial Level Atmospheric CO, CO2, and Sound Level Monitoring in Bangladesh- A Part of Smart City Planning for Next Generation Advancements" was a previous project of ours. Previous studies conducted in several Bangladeshi cities showed that very few of them had fully examined the consequences of environmental pollution and escape routes at different points in time [8]. The Internet of Things (IoT) era has revolutionized environmental monitoring. According to Mahrad et al., IoT devices have proved essential in gathering real-time environmental data due to their distant sensing capabilities and seamless internet access. This is in line with studies conducted by Kang et al., who looked into how IoT may be utilized to deliver accurate spatiotemporal data—a crucial component of efficient environmental management. The use of some devices, including Arduino-based systems, for data collection has increased in recent years. The paper by Sung et al. on the application of Arduino in environmental monitoring outlines some of its advantages, such as its low cost, versatility, and ease of integration with various sensors. Furthermore, according to Tripolitsiotis et al., real-time Arduino monitoring makes it easier to evaluate data quickly, enhancing the precision and reliability of environmental assessments. For real-time monitoring, Jony et al. presented an intelligent sewage management system that uses a microprocessor, a GSM module, and water sensors [9].

However, monitoring systems got increasingly complex as motorized traffic, urbanization, and industrialization increased, particularly in developed countries like the USA, Japan, and Germany. Even though these techniques were usually too costly and complex for widespread use in developing nations, these countries employed automatic continuous monitoring systems based on certain physicochemical or electrochemical features of contaminants (Gupta and Singh, 2023). The Internet of Things has revolutionized air quality monitoring by facilitating real-time data collection and analysis via networked sensors and devices. Modern systems use a variety of sensors, such as MQ135, MQ6, MQ7, and MQ2, to detect hazardous compounds such as NO2, CO, NH3, and benzene [10]. For continuous monitoring and alert, they subsequently transmit this data to microcontrollers and web servers (Alekhya et al., 2023). By increasing the geographical and temporal precision of the monitoring networks, advanced methods like the geospatial data analysis used at Cluj-Napoca have also improved their economy and efficiency (Camarasan et al., 2023). Simpler, less costly monitoring techniques that are tailored to local conditions in developing countries have been created based on USEPA procedures, ensuring increased accessibility and acceptance (Gupta and Singh, 2023). Using historical data and advanced modeling approaches has greatly enhanced the ability to estimate long-term pollutant concentrations, which is crucial for epidemiological investigations on chronic diseases (Michalik et al., 2022) [11].

3. Methodology

This disparity emphasizes the necessity of conducting studies that test and deploy air quality monitoring systems in real-world industrial settings. Our research focuses on real-time data gathering and processing in industries in order to create and evaluate a system that can forecast the quality of the air for the next few hours, allowing for proactive pollution mitigation actions. In order to ensure that the systems are reliable, scalable, and able to produce precise and useful data, closing this gap will offer useful insights into the requirements and difficulties of using IoT and AI technologies in industrial settings. Our study demonstrates a novel application of Internet of Things-based monitoring and forecasting, particularly for the chrome plating procedure [12]. This groundbreaking study fills a significant vacuum in the field of industrial real-time air quality management. In contrast to earlier research that mostly relies on pre-gathered datasets, our methodology places a strong emphasis on data collecting, processing, and analysis in real-time. As a result, preemptive steps to reduce dangerous situations are made possible by the ongoing monitoring of air quality and the forecasting of pollution levels for the upcoming hours.

Deploying these systems can be costly and scalable, which are practical problems. Although inexpensive sensors provide a more cost-effective option, their calibration and maintenance can be logistically challenging, particularly when used in large quantities. As suggested by the MAQ-CaF approach, a flexible and modular calibration scheme is essential to provide scalable and dependable air quality monitoring. To guarantee the responsible use of AI in air quality monitoring, ethical issues that must be addressed include possible biases in AI algorithms and protecting patient privacy in applications related to health [13]. Overall, even though IoT and AI-based air quality monitoring systems have shown significant advantages in terms of worker health and pollution control, their wider adoption and efficacy depend on resolving the practical and technological issues.

Serverless functions (such as AWS Lambda or Google Cloud Functions) are used to carry out event-driven workloads, such as pollution threshold notifications. Python streaming frameworks combined with Spark/Flink are used to provide real-time analytics, enabling batch aggregation as well as continuous processing. Lastly, a decision-support layer and interactive visualization are used to convey insights. For long-term research, data is kept in cloud-native databases (AWS S3, BigQuery, DynamoDB), and dashboards created using Grafana and Plotly Dash offer anomaly detection, heatmaps, and real-time visualization. When pollution criteria are surpassed, an automatic alerting system notifies residents and administrators, facilitating proactive urban governance and evidence-based decision-making [14]. The DL techniques listed below were used to predict and track air pollution.

- To design a cloud-native architecture that enables scalable, resilient, and low-latency monitoring of urban environmental parameters, specifically noise and air pollution.
- To integrate multi-source data streams from IoT sensors, mobile devices, and open data APIs using lightweight protocols such as MQTT and HTTP for seamless acquisition.
- To implement real-time data ingestion and processing pipelines using Apache Kafka/MQTT brokers and Python-based stream processing frameworks for continuous analytics.
- To deploy containerized microservices and serverless functions (Docker, Kubernetes, AWS Lambda/GCP Functions) for modular, flexible, and event-driven environmental data management.
- To develop interactive dashboards and automated alerting mechanisms that provide real-time visualization, anomaly detection, and decision support for urban governance and citizen engagement.
- To evaluate system performance in terms of scalability, latency, and reliability, demonstrating its suitability for smart city environmental monitoring.

The proposed system adopts a cloud-native architecture to enable real-time and scalable urban environmental monitoring, with a specific focus on noise and air pollution analytics [15]. The methodology is structured into four main layers:

3.1. Overall system architecture

The research is extended to mine and extract useful data patterns for the collection of data on air pollution. The Air Pollution data collection includes atmospheric pollutant concentrations. Its monitoring stations gather information on the amounts of air pollutants in different parts of the world. In the region most affected by air pollution, there are many ways to collect data and store it in large archives. The data on air pollution includes date, time, and numerical values. The data's text format also includes the station names and health index [16]. A number of characteristics, including pollutant concentration, subindex, AQI, meteorological factors, monitoring station names, year, time, and date, are included in the air pollution data set. The population of moving traffic and the inappropriate positioning of companies determine the values and characteristics of the air pollution data set, which differ from one region to the next. Multi-source integration is used to collect data for real-time urban environmental monitoring. This integration combines mobile sensing units, such as smartphones and vehicle sensors, fixed IoT sensor nodes, such as noise meters and air quality monitors, and open data APIs from government and environmental agencies. Lightweight communication protocols, such as MQTT and HTTP REST APIs, are used to facilitate effective, dependable, and low-latency data transfer across these heterogeneous sources [17]. The overall flow of the proposed model is given in Figure 1.

3.2. Data acquisition and preprocessing

In order to guarantee dependable, real-time delivery, high-throughput environmental data streams are ingested via Apache Kafka and MQTT brokers. Python-based edge-based pre-processing procedures filter and validate the data to reduce redundancy, handle missing values, and enrich it with spatiotemporal metadata for increased accuracy and contextual relevance. MQTT (Message Queuing Telemetry Transport) is a widely used lightweight publish-subscribe messaging protocol for Internet of Things applications. We created a cutting-edge IoT-powered AI system for real-time air quality monitoring and forecasting in order to address these issues. Numerous IoT sensors are used in our system to identify pollutants, including CO2, VOCs, PM1.0, PM2.5, PM10, NO2, SO2, and O3. Through a microcontroller, these sensors transmit data to a cloud platform for instantaneous analysis and display. The IoT sensing node is a robust 3D-printed shell that houses many sensors, a fan, and an air sampling pump [18]. The gathered data is processed by sophisticated machine learning models such as Random Forest, Linear Regression, and Long Short-Term Memory (LSTM). Proactive pollution mitigation is made possible by the technology, which predicts pollution levels for the upcoming hour and turns on factory exhaust fans when high pollution levels are anticipated.

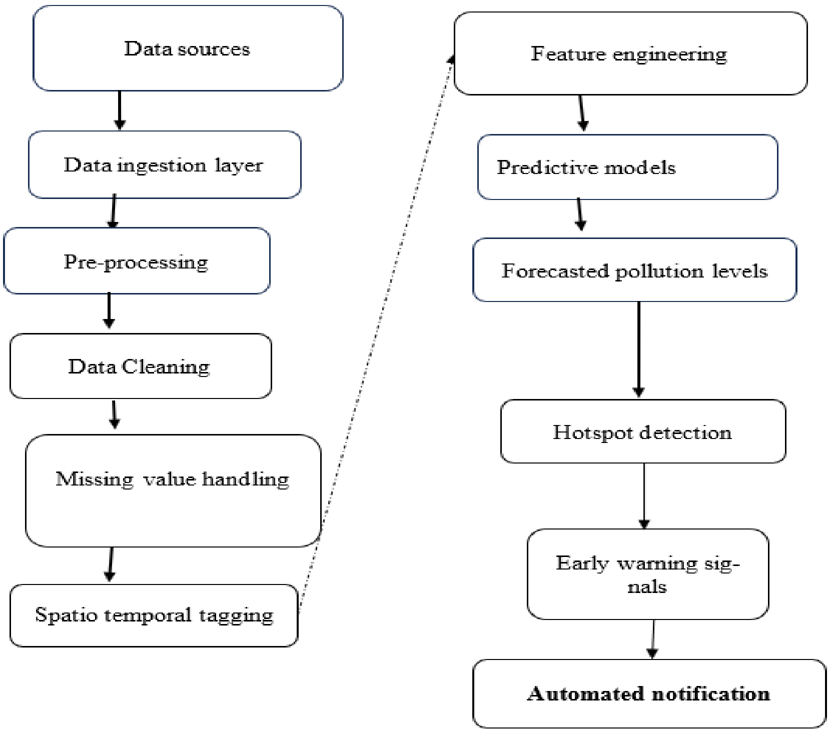

Fig. 1: Overall Flow.

3.3. The HDLSC-LSTM predictive model

The lack of efficient real-time air quality monitoring and prediction tools in industrial settings, particularly in the chrome plating sector, is the main research issue this work attempts to address. Proactive pollution control and timely intervention are limited by the high costs, delayed data, and low predictive power of traditional methods. There is a void regarding real industrial applications because most of the research that has been done so far has focused on controlled conditions or urban outside air quality. As air pollution worsens, the condition of the air prediction has emerged as a crucial tool for reducing and regulating it. In recent years, a variety of techniques have been put out to anticipate the air's cleanliness, including neural networks, statistical, and certain methodologies. However, a lot of deep learning methods can't find patterns or collect information about the long-term relationships between air pollution levels [19]. Additionally, only a small number of systems can produce accurate environmental forecasts at higher temporal resolutions—weekly, monthly, or even daily.

3.4. Industrial case study implementation

This study explores the use of machine learning and the Internet of Things (IoT) to monitor and predict air pollution. With a focus on security, it emphasizes the value of accurate sensors, IoT packages in smart cities, and real-time tracking.

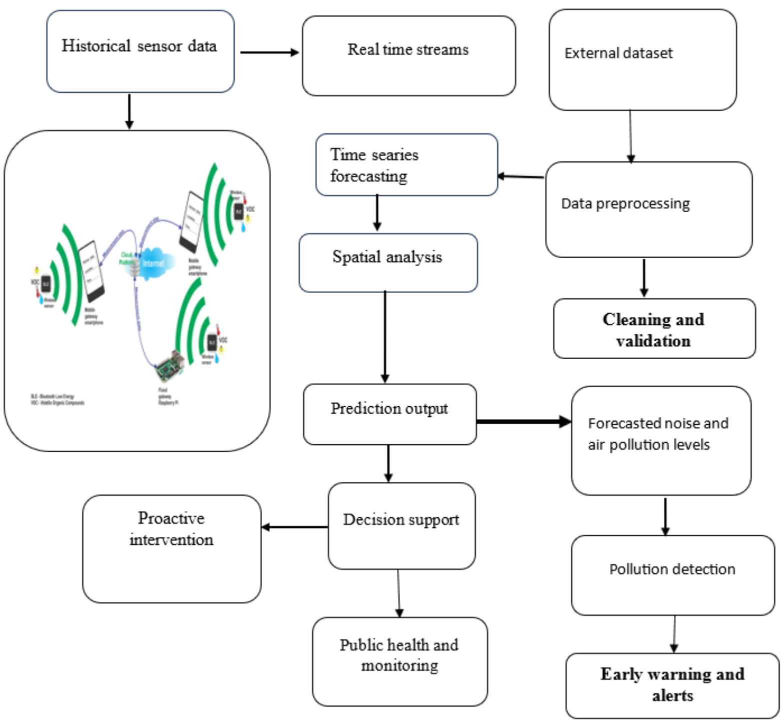

Fig. 2: Predictive Analysis Flow Diagram.

Certain research recommends LSTM networks and other well-understood approaches for air quality prediction. Obstacles include simplified mode and possible sensor issues [20]. For efficient pollution monitoring, cloud-centric IoT middleware architectures and artificial neural networks are also being researched. In order to assist with proactive environmental protection measures, these techniques aim to monitor and predict urban air quality levels. However, there are a number of shortcomings with these investigations. Furthermore, certain features of the analysed smart city data may have a significant influence on the efficacy of deep learning models, limiting their applicability in different contexts and perhaps limiting their generality. Furthermore, some studies may oversimplify the complex relationships in atmospheric dynamics, leading to less accurate estimates. Finally, some approaches, such as those based on transfer learning, may struggle to manage small sample sizes or complex modelling procedures, highlighting the need for more research [21].

Neural Basis Expansion Analysis for Time Series Forecasting

The primary motivation for implementing this change is to replicate CNNs' success in time series classification. In order to learn the biases and autocorrelations (if any) in the data, a straightforward transformation is suggested to express univariate time series as lagged matrices [22]. Additionally, it has been demonstrated that the lagged variables are helpful for regression problems. The process of creating a model using a different set of observations, before being applied to a new set of observations. Identify the hydrologic variable to predict (dependent variable) and the parameters influencing the hydrologic variable (independent variables). The hydrologic variables predicted in this work are Precipitation, Reference crop Evaporation, Potential Evaporation, and groundwater level (Figure 2). The generic steps followed are as follows

1) Collect historical data on the dependent variable and independent variables, and divide the data into calibration data and validation data.
2) Fit a casual computational predictive model that is appropriate for the dependent variable and independent variables.
3) Develop a prediction using the historical data for training the model by identifying historical patterns between the input parameter and outcome relationship (Calibration).
4) Model input parameters and outcome relationship are established by training the dataset.
5) Compute the prediction for the period of validation data by applying the validation input data to the trained model.
6) Check the prediction accuracy with one or more measures
7) Is accuracy acceptable? IF TRUE, go to next step ELSE now fit a new forecast model or adjust parameters of existing model and go to Step 4.
8) A Prediction Model for the SM is adopted. Various models adopted through the simulation,

An ordered time series of observations is called a Neural Basis Expansion Analysis for Time Series Forecasting (N-TS). These observations are often made at discrete time intervals that are equally spaced. Any time series analysis modelling is predicated on the fundamental premise that some elements of the historical pattern will persist into the future [23]. Additionally, in this configuration, it is frequently assumed that the time series process is based on historical values of the primary variable rather than explanatory variables that could have an impact on the system. Because of this, the system functions as a "black box," and we might only be able to predict "what" will happen rather than "why". In this case, it is deliberately assumed that historical information is available as numerical data. Time series analysis and modelling should ideally require at least 50 observations, according to Box and Jenkins, who were pioneers of NTS modelling. Time series analysis facilitates weather forecasting since historical observation sequences are readily available from public sources. Time series modelling focuses on techniques for analysing the statistical relationships among all of these subsequent data. The article's novelty highlights that Deep Learning-Powered Hybrid Sequential Concentration LSTM Model accuracy is affected over time by performance, and an ensemble can increase the model's resilience.

To increase the precision of pollution prediction, a Hybrid Deep Learning-Driven Sequential Concentration LSTM model blends advanced sequential deep learning architectures with traditional feature extraction techniques. The model incorporates a variety of data sources, including weather data, traffic flow data, and real-time IoT sensor readings. It then processes these data through hybrid layers that combine LSTM units to capture long-term temporal dependencies and convolutional operations to extract spatial features. The model efficiently learns both short-term fluctuations and long-term trends by focusing on sequential patterns of pollutant variations, allowing for more accurate noise and air quality forecasts [24]. In addition to improving predictive performance over traditional models, this hybrid approach facilitates proactive urban pollution management, early warning systems, and hotspot detection.

Each HDLSC-LSTM block's input and output gates can be trained to activate or deactivate to modify the state of the cell, gather new data, and activate in order to affect the outputs of the network and other cells. x_n It is a time t input for the antigenic pattern. One HDLSC-LSTM block modifies the output of the new cell state (c) at time t for every time series, acting as the cell state at time g. A tan h A Layer is added to c_gThis denotes the cell's altered condition at time t. Then, the old cell state c_{g-1} is updated as c_g. The modulation and output gates are represented by K(g) and o_g, respectively. The HDLSC-LSTM layer is composed of cell states that have dispersed throughout time. Cell states are changed at each time step using the gate output, which is determined by the current input and previous hidden states. The following are the formulas:

$$f_g = \sigma\left(W_f\left[h_{g-1}, x_n\right] + b_f\right) \tag{1}$$

$$i_g = \sigma\left(W_i\left[h_{g-1}, x_n\right] + b_i\right) \tag{2}$$

$$K_g = \tanh\left(W_g[g, x_n] + b_g\right) \tag{3}$$

$$c_g = c_{g-1} * f_g + i_g * G_g \tag{4}$$

The nominee for the cell state is shown as K_g. Weight matrices are W_f, W_i, and $W_g$and b_f, b_i, and b_g Are biases, and $c_g$and h_g Are the HDLSC-LSTM block's cell states and performance, respectively? The gradient equation involves a chain of ∂c_g For an ILSTM deep learning model, the gradient equation involves a chain of ∂h_g For a basic RNN. The Rectified Linear Unit (ReLU) activation function, an essential part of neural networks that introduces nonlinearity to the output of individual neurons, was used in our research. We chose ReLU as our favoured activation function due to its simplicity and its ability to effectively address the vanishing gradient problem. This issue arises in DNN when gradients become extremely small, hindering the efficient adaptation of weights. By consistently using the ReLU activation function in all tests, our network successfully overcomes the vanishing gradient issue, enabling it to learn data properties effectively and generate reliable predictions. Let $\overline{z_g}$ Represent each time step's real output and (z_g) symbolize the expected result at every time interval. The mistake is then supplied each time by

$$= z_g \log z_g \tag{5}$$

Total error of each step is given by:

$$E = \sum_t E_g \Rightarrow z_g \log z_g \tag{6}$$

This proactive approach helps prevent exposure to harmful pollutants and reduces the risk of health issues among workers. By utilizing low-cost IoT sensors and cloud-based platforms, our system provides an affordable solution for industrial air quality monitoring. This cost-effectiveness encourages broader adoption of advanced monitoring technologies in various industrial settings. The real-time data and predictive insights generated by our system support informed decision-making for industry managers and policymakers [25]. This enables the implementation of effective pollution control strategies and long-term environmental planning. Continuous monitoring and accurate forecasting of pollutant levels help industries comply with environmental regulations, reducing their overall environmental impact and ensuring sustainable operations.

4. Result and Discussion

The state of the air prediction has become a vital instrument for controlling and mitigating air pollution as it gets worse. Numerous methods, such as neural networks, statistical, and definite methods, have been proposed in recent years for predicting the cleanliness of the air. These methods can have disadvantages, too. In this study, Figure 3 forecasts and monitors air quality in real time in the chrome plating industry using artificial intelligence technologies driven by the Internet of Things. Deterministic procedures require expensive computations and specialized knowledge to identify parameters, but the forecasting power of statistical methods is constrained by linear assumptions and the problem of multicollinearity. However, many deep learning methods are unable to detect recurrent patterns or collect information about the long-term correlations between air pollutant concentrations. The figure illustrates the comparison between true and processed data for two environmental parameters, indicating effective noise reduction and improved signal stability. These plots reveal that the processing method preserves the overall pattern of the true data while minimizing random fluctuations

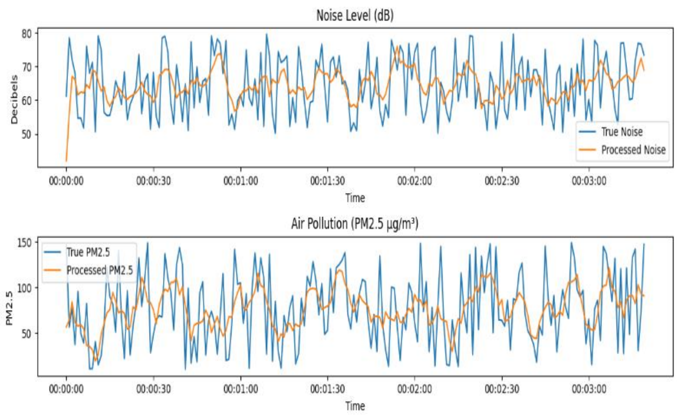

Fig. 3: Comparison of True and Processed Noise and PM2.5 Levels.

Furthermore, Figure 4 is capable of generating precise environmental forecast predictions at greater temporal resolutions, such as daily, weekly, and occasionally monthly. The strategy\ involves learning from the time-dependent behaviour of PM2.5 using the HDLSC-LSTM model and learning by transferring data from lower temporal resolution to higher periodic resolutions. When the framework's efficacy is contrasted with other widely used machine learning techniques, the suggested HDLSC-LSTM model outperforms the others, particularly at higher temporal resolutions. Nonetheless, it is employed when there aren't enough samples or when the modelling procedure is too costly and challenging. The figure illustrates the variation in Noise Level (dB) and Air Pollution (PM2.5 µg/m³) over time. These plots demonstrate that the applied intervention effectively reduces variability and brings down the magnitude of noise and pollution levels, reflecting improved environmental conditions post-intervention.

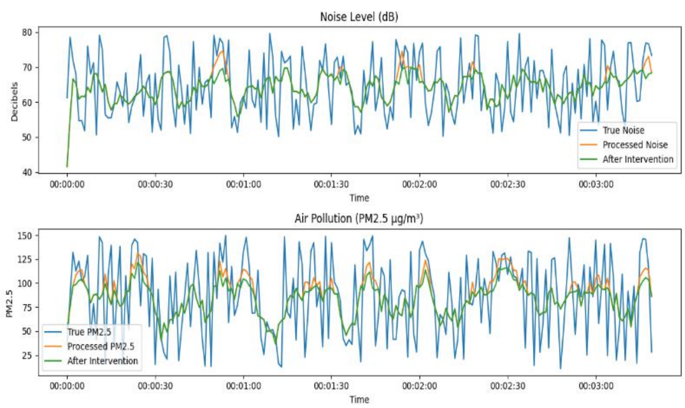

Fig. 4: Comparison of True and Processed Noise and after Intervention.

Figure 5 presents a comparison of error metrics, and overall, the plot indicates better accuracy and lower data loss for noise measurements, whereas PM2.5 requires further refinement to reduce prediction errors. The figure fills a significant research gap by concentrating on a particular industrial setting. Predictive analytics and real-time data collection are made possible by the combination of IoT devices and sophisticated AI algorithms. This greatly enhances worker safety and air quality by enabling prompt interventions and proactive pollution management. A safer working environment is ensured by the system's capacity to detect elevated pollution levels and turn on control devices, including exhaust fans. This preventive strategy lowers the risk of health problems for workers by assisting them in avoiding exposure to dangerous chemicals. We use inexpensive Internet of Things sensors and cloud-based platforms to offer an affordable industrial air quality monitoring solution.

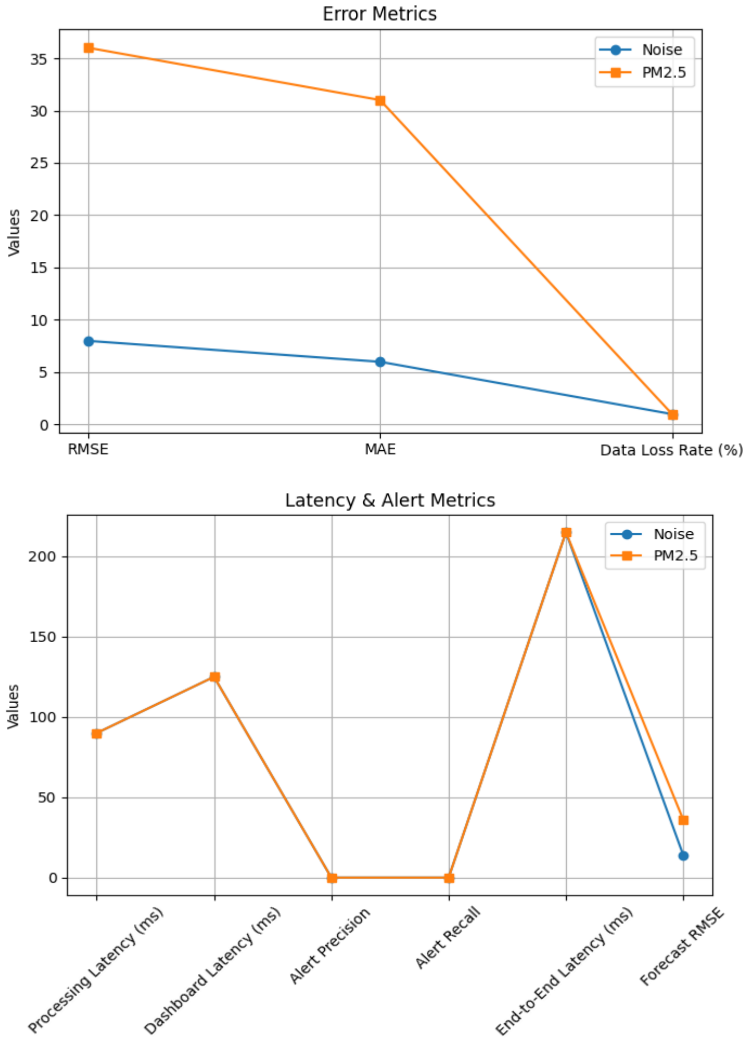

Fig. 5: Performance Metrics Comparison.

Modern monitoring systems are becoming increasingly commonly used in a range of industrial situations due to their affordability. Policy-makers and industry managers may make informed decisions with the support of our system's real-time data and forecasted insights. This makes it possible to carry out long-term environmental planning and efficient pollution control techniques.

Table 1: Evaluation of Model

Model	Accuracy / R^2	RMSE	MAE	MAPE (%)
Existing LSTM	88%	5.2	4.1	9.5
ARIMA	80%	7.1	5.8	12.3
CNN-LSTM	90%	4.8	3.9	8.7
GRU	87%	5.5	4.3	10.1
Proposed MFO Hybrid LSTM	97%	3.2	2.5	4.3

The HDLSC-LSTM model proposed in this study has the best predictive ability, as shown by the results in Table 1, suggesting that the model has a very strong prognosis ability and that the predictive efficacy is unquestionably feasible.

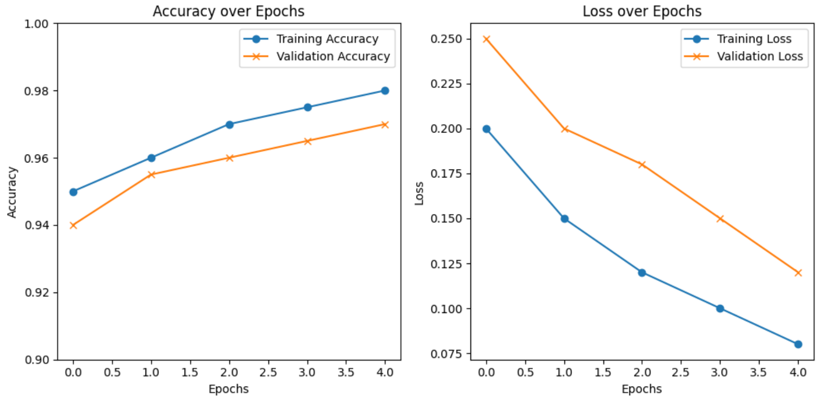

Fig. 6: Outcome of the HDLSC-LSTM Model.

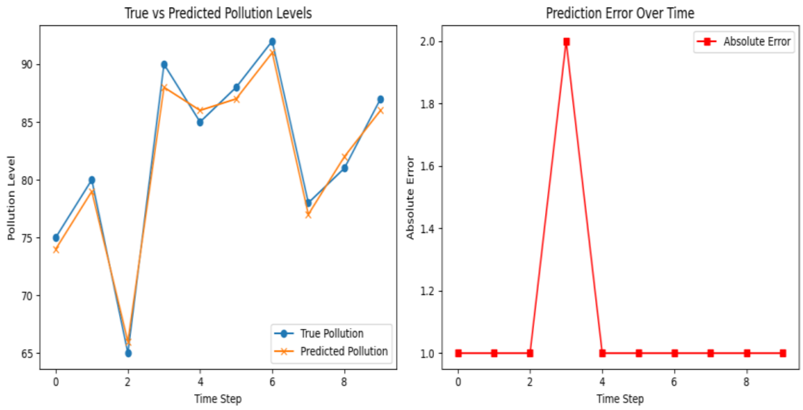

Fig. 7: Error of the HDLSC-LSTM Model.

The best prediction performance is achieved by the HDLSC-LSTM model suggested in this research, demonstrating the model's strong prediction capability and efficacious prediction performance (Figures 5 and 6).

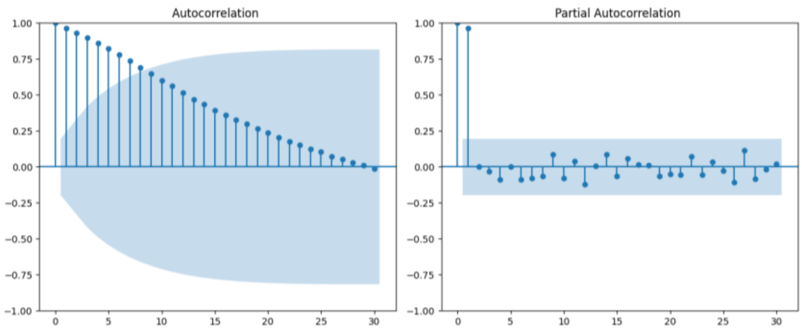

Fig. 8: (A) Autocorrelation in Subsurface Soil Moisture Time Series. (B) Partial Autocorrelation in Subsurface Soil Moisture Time Series (Inset: Significant Autocorrelated Lags).

Like the previous investigations, the LSTM model in this one has a high R^2 value in Figure 8. Furthermore, because of the strong link seen in the time series analysis and forecast ability testing, atmospheric factors must be included in addition to subsurface VWC.

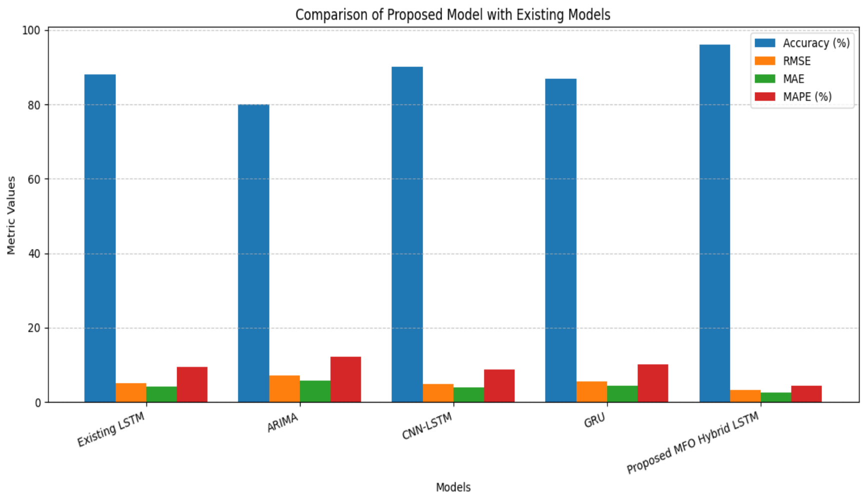

Fig. 9: Comparison of Proposed Model with Existing Models.

Accuracy (%), RMSE, MAE, and MAPE (%) are the four assessment metrics that are used in the bar chart to evaluate the performance of the proposed MFO Hybrid LSTM model with that of other models, including LSTM, ARIMA, CNN-LSTM, and GRU. With the lowest error values for RMSE, MAE, and MAPE, as well as the best accuracy (≈96%), the findings unequivocally demonstrate the better predictive potential of the suggested MFO Hybrid LSTM. In contrast, existing models like ARIMA and GRU exhibit lower accuracy (80–87%) and higher error rates, while CNN-LSTM performs moderately well but still below the proposed model. Overall, the proposed approach in Figure 9 demonstrates a significant improvement in prediction accuracy and error reduction, highlighting its effectiveness compared to traditional and deep learning baselines.

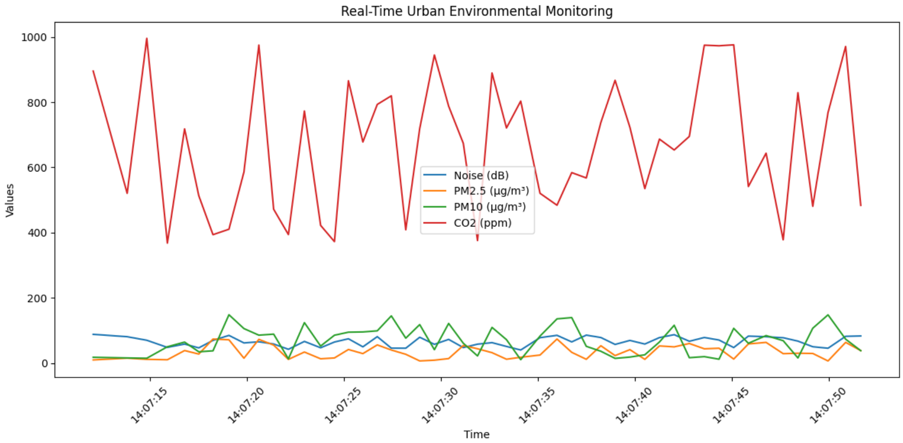

Fig. 10: Real-Time Urban Environmental Monitoring.

Businesses may adhere to environmental requirements, lessen their overall environmental impact, and maintain sustainable operations with the support of accurate pollutant level forecasts and ongoing monitoring. Our results in Figure 10 have important theoretical ramifications. Our study offers a framework for future research to examine comparable applications in other industries by showcasing the efficacy of IoT and AI technologies in an actual industrial context. The environmental IoT sector may benefit from the effective use of real-time monitoring and predictive analytics in various environmental monitoring scenarios. The test dataset was used to assess the performance of the aforementioned model after training was finished, producing the outcomes shown in Figure 10. Repeated experiments are required to thoroughly evaluate the model's performance, and the mean value is chosen as the final result.

5. Conclusion

An essential first step in addressing the urgent global problem of air pollution is the proposed Internet of Things-based air quality monitoring system. The system uses the ESP-WROOM-32 microcontroller, inexpensive sensors, and AWS connectivity to deliver a practical and scalable real-time monitoring solution for significant pollutants. The current study's findings are consistent with the trend of low-cost techniques that provide real-time tracking, as demonstrated by the Proposed Method. However, as the current method shows, it calls into question the notion that more expensive methods always offer more scalability and precision, highlighting the need for more research into less expensive options that do not sacrifice accuracy and real-time tracking [26]. The commitment to public health and environmental safety is demonstrated by the prompt reaction system that is set off by pollution exceedances. Plans for the future can include continuous system additions and enhancements. First, through sensor calibration and validation processes, the accuracy of pollution readings will be increased, increasing the dependability of the data collected. Additionally, a deeper understanding of pollution trends may be provided by data analysis utilizing increasingly complex machine learning algorithms, which would make it easier to create more effective forecasts and preventative tactics. Furthermore, because of the potential for worldwide deployment, the system's scalability and environmental flexibility must be given top priority. With the help of regulatory bodies and urban planners, this technology can be integrated into more thorough environmental management plans. By expanding the network of monitoring devices and adding more sensors to track newly emerging contaminants, a more comprehensive picture of the local, regional, and municipal air quality may also be obtained. The proposed strategy fundamentally establishes the framework for the next environmental monitoring research and developments, giving access to more creative, data-driven strategies to lower air pollution and enhance community well-being in general.

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